Explainable Suicide Risk Prediction with DeepFusion: A Hybrid Intelligence Approach

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***Abstract*—Social media sites have emerged as a significant and trustworthy source of information, with users frequently sharing their feelings, thoughts, and opinions on them. These platforms may extract specific interests and trends from user-generated material in real time by utilising developments in data mining technologies. In terms of gaining useful insights from such data, deep learning models have outperformed typical machine learning models. Three deep learning techniques—Deep Neural Network, Long Short Term Memory, and a CNN-LSTM hybrid model—are used in this study to estimate the likelihood that a tweet on X (previously known as twitter)may contain suicidal content.The feature extraction process relies heavily on the CNN component of the hybrid model. Using convolutional and max-pooling layers, it successfully recovers higher-level characteristics from the textual input. But the state-of-the-art natural language processing model LSTM excels at maintaining long-short-term relationships within tokens and sequences.Our research demonstrates that the CNN-LSTM hybrid model performs better than traditional deep learning models across a number of evaluation metrics, including accuracy, precision, sensitivity, and f1 score.**

Keywords—ANN,LSTM,CNN,CNN-LSTM, Sentiment Analysis,Suicidal Risk, Hybrid Neural Network

I. Introduction

Each year over the world almost 703,000 people commit suicide and many more people attempt suicide [1].From year 2000 through 2018 rate of suicidal incidents in the United States increased 30%. This rate is increasing since 2006 and declined in 2019.Suicide was one of the leading causes of mortality in the United States in 2020, accounting for 45,979 deaths, with one death occurring every 11 minutes. Estimated 12.2 million American adults considered suicide seriously, 3.2 million plotted a suicidal attempt, and 1.2 million attempted suicide. For adults of 25-34 and children of age group 10-14 suicide was second largest cause of death. For overall 10-64 years old age group people in the states it was top 9 leading cause for suicide [2].Suicidal thoughts, plans, and behaviors are those that someone has with the intention of ending their own life. Depression and suicide are associated. 60% of suicide attempts are influenced by major depression. [3].

Traditional risk assessment settings of suicidal or self harming potential for individual is a very inaccurate and time-consuming task. Few settings where suicidal risks are estimated such as mental heath centers, traditional methods for evaluating risk uses survey screening tools,the Patient Health Questionnaires and the Columbia Suicide Severity Rating Scale, for instance. Many tools have been created and tested over the past 50 years on a variety of people, however studies have revealed that these tools are not accurate. Large datasets used in research in fields like machine learning and natural language processing suggest very promising results for the healthcare industry. In particular, youth have trouble responding to these social desirability screening techniques, exhibit a lack of comprehension and involvement with the rater [4].

Because of the intellectual and psychological characteristics of natural languages, text processing becomes more challenging. The two types of NLP applications are separated. In the first kind of application, the main area of concern is computational tasks like spell checks, grammar checkers, and machine translations. The second type of application emphasizes the linguistic component further, with linguistic resemblance to human languages as the main goal. It does, however, also identify and change theoretical and psychological data. The second category includes poetry, story creation, sentiment analysis (SA), and intelligent information retrieval. SA is the process of drawing theoretical and psychological information from texts. Lexicon-based and machine learning techniques are the two main kinds of sentiment analysis methods. The fundamental principle of lexicon-based SA is to develop a vocabulary for a particular field of study and then categorize texts using that lexicon. Machine learning methods are used in contemporary SA procedures. A substantial amount of labeled data is required for statistical learning approaches, which are also utilized in addition to deep learning.Both often occurring and challenging is the issue of sentiment analysis in natural language processing. Many recently released blogs and social networking sites collect data utilizing automated ways on opinions, trends, assumptions, and attitudes [5]. Performing Sentiment Analysis researchers, business corporals and different organisations can easily sort out their target insights like tends, product reviews, public opinions and so on according to their interest. We wanted to utilize the second nature of NLP application to predict which user is in depressed mental state to prevent him/her from self destructive acts.

Along with these our legacy works has inspired us to work on another mental health issue. We worked on sleep level stress prediction and it's effect on hart failure [6]. We also have worked on athletic fitness tracking to monitor their physical helth [7] Our group has vast experience of working with machine learning classifiers

II. Literature Review and Related Works

Pandi [8], and their colleagues established a connection between depression and disturbances in the circadian rhythm. Researchers conducted a content analysis of Twitter and found a continuous rise in rumination and emotional content among those with depression between the late night to early morning hours.

The researchers employed various conventional classifiers to classify the author of a single tweet as either suffering from depression or not. Each verified Twitter account user had a maximum of 3200 tweets retrieved. The user employed four separate categorization methods: Random Forest, Naïve Bayes, Logistic Regression, and Support Vector Machine. The utilization of cutting-edge neural network architectures in natural language processing (NLP) has resulted in a novel approach for detecting Twitter posts that indicate a potential risk of suicide. Deep learning models have surpassed standard machine learning models in terms of performance. Aldhyani et al. [9] performed a comparative investigation to showcase the effectiveness and capacity of the routes utilizing the LSTM classifier and five other traditional ML models.

Rahman et al. [10] applied NLP to analyze sentiment that emphasises on depression on twitter. After then, tweeter posts are classified as positive or negative, based on a list of lexicon to predict the number of users are prone to show depressive state.They created dataset using ten thousands posts accumulated with the help of twitter API and used Naïve Bayes classifier for estimating sadness with 83% accuracy. Tadesse et al [11] put forward a data analytic statistical model for depression recognition. They analyzed social platform posts like Facebook and Twitter for their study. The researchers employed various conventional classifiers to classify the author of a single tweet as either suffering from depression or not. Each verified Twitter account user had a maximum of 3200 tweets retrieved. The user employed four separate categorization methods: Random Forest, Naïve Bayes, Logistic Regression, and Support Vector Machine [12]. The utilization of cutting-edge neural network architectures in natural language processing (NLP) has resulted in a novel approach for detecting Twitter posts that indicate a potential risk of suicide. Deep learning models have surpassed standard machine learning models in terms of performance. Modeling of data that occurs in a specific order or sequence. The recurrent neural network (RNN) is purposefully designed. LSTM is an advanced recurrent neural network that is particularly effective at capturing extensive connections between texts. In a study conducted by Sawhney et al., it was shown that CNN-LSTM-based deep learning techniques are more effective than other classifiers, such as standard machine learning and deep neural architecture, in evaluating the likelihood of suicide. Aldhyani et al. [13] performed a comparative investigation to showcase the effectiveness and capacity of the routes utilizing the LSTM classifier and five other traditional ML models.

Aldhyani et al. [9] revealed a comparative study, where the LSTM classifier along with five different traditional ML models evidenced the effectiveness and ability of the pathways. This findings uncovered one of the leading standard for observing the suicide risk on Reddit SuicideWatch and Twitter. In the early years, CNN deep learning techniques such as convolutional, pooling, and nonlinear layers have been widely used to solve a variety of NLP applications and have shown to be more efficient than traditional NLP techniques. He et al. [14] used a mix of ConvNet and Bi-LSTM, a new deep neural network model has been proposed to address the quantification problem of a semantic textual comparison. Mccrae et al. [15] provided a successful mixed technique for managing SA that blended a primary information recovery approach with a quick profound method. In this article, we provide a model for classifying articles that may be at risk for suicidality using CNN and LSTM neural architecture.

III. Study and Proposed Methods

We employed three different deep learning models—MLP, LSTM, and CNN-LSTM—to early predict the likelihood of suicide using Twitter data. The use of more than two additional models is done to highlight how superior our proposed model is. For better understanding, a comparison of several evaluation ratings is also provided.

A. Word Embedding

The representation and processing of words serve as the foundation for NLP applications. Each word is represented as a real-valued vector in a specified vector space when word embedding is used. The technique is sometimes referred to as deep learning since each word is assigned to a different vector and its values are evaluated in a way akin to that of a neural network. Using all distinct words, a vector is first defined in this process. Then each word t^{th} can be presented as:

$$x_t \in R^d$$

Where d is dimension of the word vector. Final whole input text presented as

$$X = [x_1, x_2, x_3, ..., x_T] \in R^{Txd}$$

Here T stands for length of total words. Word embedding overcomes some issues of one-hot encoding like problem of presenting similarities among words and dimensional disaster.

B. Deep Neural Network (DNN)

This is a simple neural network structure, stacked one dense layer of neuron to another dense layer of network. DNN sometimes called as Vanilla Neural Network specially when there is no hidden layer.An input layer, a hidden layer, and an output layer are the three node layers that make up a DNN. Figure 1 depicts this and the nonlinear mapping between the input and output vectors. By superimposing a large number of fundamental nonlinear transfer functions, the multilayer perceptron may approximate extremely nonlinear functions. [16]. After analyzing each row of input, deep learning models

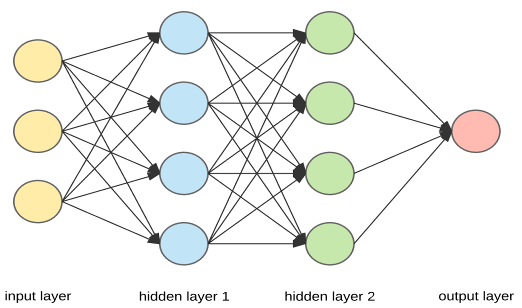

Fig. 1: Architecture of a simple deep neural network. [17]

adjust the connection weights in order to learn based on how inaccurate the output is in comparison to the expected result.

$$J(w) = \frac{1}{2m}\sum_{i=1}^{m}(y - \hat{y})^2 \quad (1)$$

Here y is actual output, $\hat{y}$ = predicted result, (y - $\hat{y}$) = error and $J(\theta)$ = total error or cost function.

$$\Delta J(w) = -\alpha\frac{\partial J(w)}{\partial w_j} \quad (2)$$

$\Delta J(w)$ = Gradient term, α = learning rate, w = weight parameter.

$$w_j := w_j - \alpha\frac{\partial J(w)}{\partial w_j} \quad (3)$$

This is the gradient descent algorithm, which starts with some initial w, and repeatedly performs the update the parameter for minimizing the J(w).

$$y(x) = \frac{1}{1 + e^{-x}} \quad (4)$$

Above equation is sigmoid activation function, which converts weighted output of the node/nodes in the range of 0-1.

$$R(x) = max(0, x) \quad (5)$$

This function is called ReLu (Rectified Linear Unit) function. For hidden layers this activation function best choice for most of the cases.

$$ReLU(x) = \begin{cases} 0 & x < 0 \\ x & x \geq 0 \end{cases} \quad (6)$$

This one is another form of the ReLu activation function.In our deep neural network model, we have used this activation function for all the hidden layers. In our DNN each layer used ReLu (Rectified Linear Unit) as activation function except the output, which uses sigmoid activation function.

C. LSTM (Long-Short Term Memory)

LSTM is a particular type of RNN structure employed in deep learning with the expectation of identifying, editing, and predicting sequential entry. LSTMs commonly contains three gates that control the incoming and outgoing of information to and from their memory units. The LSTM network outperforms the RNN model in terms of its capacity to handle long-term dependencies. It includes a memory cell that takes care of transmission of data to and from each gate. An important feature of LSTM is its capacity to circumvent the problem of vanishing gradient [18]. The three gates that in general

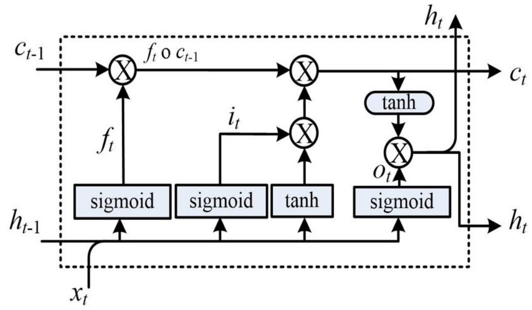

Fig. 2: Architecture of LSTM cell [18]

regulate the information flow into and out of LSTMs are input, output, and forget. The "input gate" monitors the amount of new data that is being inserted into the cell memory. The "forget gate" controls the duration of value storage in cell memory. The output gate also regulates the memory value's volume, which has an impact on how the block's output is turned on. Each of these attributes is detailed in Fig. 2. Our LSTM model received a layer of 300 LSTM units. Every gate does its own computations. The LSTM layer is composed of input sequences $X = (x_t)$ with a d-dimensional word embedding vector, where H is the quantity of LSTM hidden layer nodes [19].

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f) \quad (7)$$

This calculation is performed in forget gate f_t to control the information sent to memory cell, where W_f and U_f stands for weight matrices and b_f is a bias vector applied to the forget gate.

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \quad (8)$$

Input gate i_t, which decides what new information to be kept in memory cell, performs it's computation like above, where b_i is the bias vector for input gate.

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \tag{9}$$

Eq. 9 shows the calculation step of output gate o_t where b_o is the bias vector for output gate. Eq. 7,8 and 9 performs almost similar type of mathematical calculations to select or forget using logistic sigmoid function σ, which converts values to either 0 or 1.

$$u_t = tanh(W_u x_t + U_u h_{t-1} + b_u) \tag{10}$$

tanh layer u_t decides the importance of the information, after successive update or ignore through.

$$c_t = f_t \odot c_{t-1} + i_t \odot U_t \tag{11}$$

Memory cell c_t, performs above mention equation to hold in each step and confirms long distance correlation with new input. The operator $\odot$, stands for element-wise multiplication.

$$h_t = o_t \odot tanh(c_t) \tag{12}$$

At the time t, based on output cell state, memory cell exposes the volume of information which is mentioned by the hidden unit h_t [20].

D. CNN-LSTM Hybrid Model

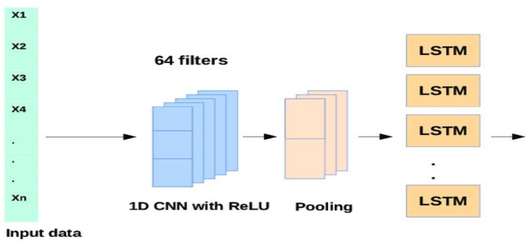

Fig. 3: Architecture of CNN-LSTM Hybrid Model

For predicting suicidal risk from twitter data we tried to exploit robustness and updated abilities of both this two networks and used unified architecture combining CNN and LSTM for out selected data.

In the last section, we discussed about LSTM architecture. Most updated variant of RNN for feature extraction, similarity analysis and long-term correlation mapping in text. Convolutional layer has a strong performance ability, part of CNN. Very beginning CNN was designed for image recognition. After this neural network is developed gradually it become versatile and used in text classification with significant outcomes [21].

If CNN is applied in well processed text data, this model learns and recognizes pattern that would lost in feed forward network.CNN has the power of extracting features no matter of where they found in a text sequence [22].

The word embedding vector's dimension is k, and the word count is j, with $F \in R^{jxk}$ serving as the convolutional filter. A convolutional filter's output value at time step t $F = [F_0, F_1, ..., F_{m-1}]$ is as follows:

$$O_{F_t} = ReLU[(\sum_{i=0}^{m-1} x_t F_i) + b] \tag{13}$$

One word that is embedded in a vector is the word x_t. F and b are the parameters of a single filter. After that, non-linearity is eliminated using a ReLU activation function, which is mentioned in Eq. 5 [23].

Equation (13) demonstrates the extraction of features using only one filter. However, we applied a number of filters in our model to extract features from a text sequence. The probability function that included the softmax function and was used to classify x into category j is as follows:

$$P(y^i = j|x^{(i)}; \theta) = \frac{e^{\theta_j^T x^{(i)}}}{\sum_{k=1}^{K} e^{\theta_j^T x^{(i)}}} \tag{14}$$

E. Datasets

Two kind of tweets we used for our models verification. Random tweets that does not indicate depression, which is collected from kaggle and another kind of tweets which indicates depression. Due to difficulties of finding any public datasets for depressive tweets we used tweeter's official api TWINT using the keywords 'depression' to collect the depressive tweets. Datasets used for our study contains total of 14,000 rows. We divided our dataset into three section which are used for train, validation and test. Test contains 80% of the total data, validation set used 10% and test set used the rest of the data for final performance evaluation of our models.

TABLE I: Data Statistics

Train	Validation	Test
80%	10%	10%

F. Evaluation Metrics

In our evaluation procedures we mostly relied on confusion matrix, which illustrates the values of true positive(TP),false positive(FP), true negative(TN) and false negative(FN). To asses the performance of our models we considered some evaluation metrics like accuracy of the predictions using Equation (15), a harmonic average of precision and recall called F-score, expressed by equation (16). Recall estimates the proportion of correctly identified positive samples and precision is about the number of positively predicted outcomes.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{15}$$

$$Precision = \frac{TP}{TP + FP} \tag{16}$$

$$Recall/TruePositiveRate = \frac{TP}{TP + FN} \quad (17)$$

$$FalsePositiveRate = \frac{FP}{FP + TN} \quad (18)$$

$$F_1 = 2.\frac{precision.recall}{precision + recall} \quad (19)$$

IV. Results and Discussions

In our study, three methods for estimating suicide risk from tweets were applied. The numerical values of numerous evaluation metrics are displayed in the following table.

TABLE II: Results

Model Name	Accuracy	Precision	Recall	F1 Score
DNN	86.3%	54.7%	17.9%	0.260
Basic LSTM	94.3%	92.3%	91.2%	0.917
CNN-LSTM	97.2%	93.1%	92.2%	0.926

There is a discernible difference between basic-LSTM and DNN in terms of accuracy. The basic-LSTM model performs 12.82% better than DNN in terms of accuracy. Although DNN showed a decent degree of accuracy, other evaluation measures do not back up the assertion that DNN is a useful model for determining suicidal risk from tweets. The F1 score for DNN is 0.260, which is regarded as another trustworthy measure for evaluating any machine learning model. The LSTM's F1 score also shows a very encouraging result of 0.960, which is good enough to suggest LSTM as one of the models that might work well for our inquiry. The recall and precision of LSTM are evaluated using three more parameters, and they outperform DNN by 44.3 and 82.1 percent, respectively. For the bulk of the evaluation metrics in our study, the hybrid CNN-LSTM model outperforms other models. Its accuracy rating is 99.1%, which is 2.02% higher than that of the basic-LSTM model.

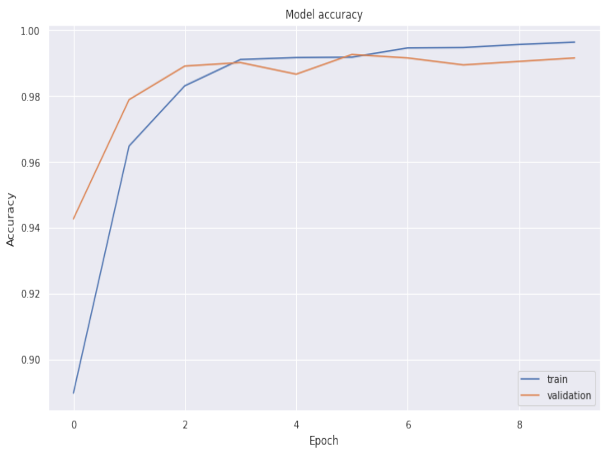

Fig. 4: Accuracy of the CNN-LSTM model for 10 epochs

From this diagram we can decide that the hybrid CNN-LSTM model is not over-fitted or under-fitted. Other evaluation metrics such as F1 score, precision and recall is extremely good for this model which are 0.926, 93.1%, 92.2% respectively.

Another interesting finding from our study is that along with hybrid CNN-LSTM model we have got very good result from basic-LSTM model also.

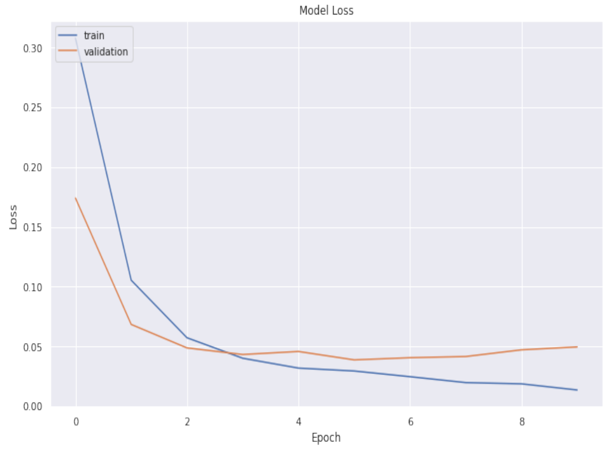

Fig. 5: Learning curve for CNN-LSTM model for 10 epochs

Above diagram illustrates the learning/loss curve for the CNN-LSTM hubrid model. From the diagram we see that validation loss is higher than training loss. Which signifies that goodness of fit of the learning curve.

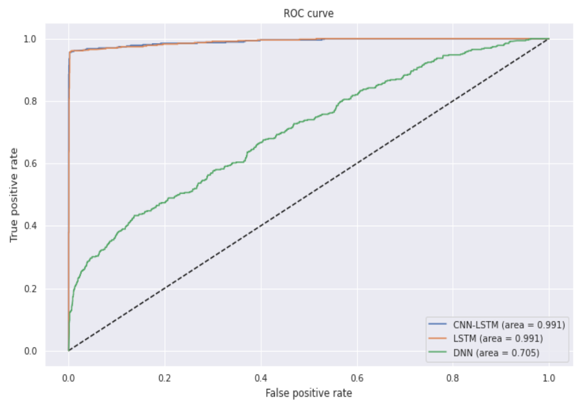

Fig. 6: AUC(Area Under the ROC Curve)

Fig. 6 is called ROC(Receiver Operating Characteristic) curve for three different model, which is showing the performance of different classification models. AUCs(Area Under the Curve) for the CNN-LSTM, basic-LSTM and DNN are 0.991, 0.991 and 0.705 respectively. For any perfect model it is 1. So we can say that for both CNN-LSTM and LSTM are suitable for suicidal risk prediction from twitter data.

V. Conclusion

Implementation of deep learning for suicidal risk prediction augmented a new direction for the researcher for early detection of suicidal risk. We have tried to contribute towards the improvement of technology in NLP and convolutional linguistic. In our study, we presented a method to identify the presence of suicidal risk in twitter posts and emphasises on recognizing most significant performance improvement approach.

Our aim was not to explore the detailed sensitivity of CNN hyper-parameters with respect to the designed decisions. But we alternatively wanted to improve the potential of CNN-LSTM classifier for suicidal risk prediction task.

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