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Deep Learning Approaches for Early Detection of Depression using Sarcasm

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Abstract:

The huge popularity of social media like Facebook, Twitter, WhatsApp and Instagram where most people can share their opinions about other people without any social dishonours. This can lead to people being depressed. Furthermore, sarcastic words have a significant impact on depression levels. As a result, early depression detection is critical. Despite the fact that depression detection was done by using algorithms such as SVC, NB, DT, and LR have been developed using the Twitter dataset and sarcastic statements. However, there is scope for improvement. The proposed model for effectively detecting sarcasm is referred to as " Sarcastic News Dataset and Tweet-based Depression Detection (SNTDD)”. The proposed model for detecting sarcastic remarks in text data uses ensemble Deep learning models and compared it with the machine learning models. The proposed model is used the ensemble model of Deep learning model and the dense layer, the model gives better accuracy and reduce the loss. Additionally, it works on positive sarcastic text to increase performance. The significance of this is that more positive indicates it has a stronger impact on mental health or raises the amount of depression. Sarcasm in study can be difficult to identify as a result of the complex relationship of both positive and negative characteristics. In contrast to signs such as tone or facial expressions, natural language processing addresses a challenge of detecting sarcasm with requiring the use of context markers. In contrast to signs such as tone or facial expressions, natural language processing addresses the difficulty of detecting sarcasm without the need of context markers. The experimental results reveal that the suggested model "Sarcastic News Dataset and Tweet-based Depression Detection (SNTDD)" is tested on the data. The model outperforms deep learning and machine learning algorithms on the news headline dataset, with an accuracy of 97.4%. Consequently, the proposed model received a 94.4% F1 score.

Keywords: Depression, Sarcasm, Support vector machine (SVM), Random Forest (RF) ,Decision Tree (DT), Logistic Regression (LR), XGboost and

Navie Bias (NB), Machine Learning (ML), Long Short Term Memory (LSTM), Convolutional Neural Network (CNN), Deep Learning (DL).

1. Introduction

Prolonged stress, which is frequently the result of extended psychological stress, can cause serious physiological problems and aggravate illnesses like depression, which is a major cause of suicide rates worldwide [1]. Globally, the COVID-19 pandemic has increased stress levels and changed lifestyles, and more people are facing mental illness, especially women [2]. Social media has emerged called a crucial channel for those looking for psychological assistance during quarantine and isolation, which has been called as the "buffer effect," given the catastrophic consequences seen in severely affected nations like the US and India [3][4]. As a result, people from different backgrounds, such as students and migrant workers, have suffered mentally during the pandemic. Some people lose their jobs, some of them are away from family, and some of them are facing problems while they are quarantined. They all are mentally disturbed. The impact of these they were moving towards the depression unknowingly. [5]. According to a WHO report, 6% to 21% [6] of the population suffer from depression, which is one of the main causes of disability worldwide. The problem is that depression is the second most prevalent illness worldwide but people are not taking it as a serious problem. People are giving more importance to physical instead of mental problems [7]. It requires medical treatment. Due to a lack of awareness about mental health people are not getting financial support for such type of treatment, especially in underdeveloped nations with inadequate healthcare systems [8]. The diagnosis of mental health is expensive and time-consuming in the developing countries. To provide Efficient treatment of depression involves early detection of symptoms. Because of access issues and cost limitations, this reliance on conventional diagnostic techniques frequently results in patients going untreated. To close this gap and enhance outcomes for people with depression, low-cost, non-invasive diagnostic techniques must be developed [9]. Social media has emerged as a popular forum for sharing people's views; even short messages can reveal a lot about a person's mental health. Studies examine the effects of social media on a range of social dynamics and depression indicators, including problems in relationships, drug abuse, self-harm, bullying and mental disorders. [10][11].

Social media is a platform to share positive and negative views. Where the emotions can identify using text and the text sequences. It is the most important tool for identifying the depression. It reaches global and high user engagement making it a promising tool for diagnosing depression. Because emotions in text sequences are long-term dependent, analysing them might be difficult [12]. Recent research in the analysis of emotion has been done on the sequential text and the text patterns. The Long Short-Term model (LSTM) is used to take text patterns sequentially. However, recent improvements in emotion analysis have concentrated on identifying sequential text patterns, particularly in online health forums where psychiatrists and other specialists answer depression-related inquiries.

In the field of mental healthcare, emotion detection is essential [13] [14][15], and deep learning models like LSTMs, CNNs and neural networks are used to efficiently identify multiple emotion categories [16]. To capture the subtleties of texts on mental disorders, multifaceted strategies that include attention models and long-term mutual dependence are essential. While earlier research has identified fundamental emotions, more current endeavours seek to associate emotions with psychological disorders by employing deep learning techniques to identify emotions associated with physiological and semantic characteristics in text sequences [17]. The above work analyse as: The main areas of interest include emotions in mental health, how they affect behaviour, and how long-distance semantic knowledge can be retained. To do this, each word in the text sequence is given an attention mechanism, and word embeddings are used to collect semantic information. Furthermore, to enhance comprehension of their influence on mental health, more weight is given to evaluating lengthy texts rather than brief ones and integrating a variety of emotion categories into the text flow. Psychological elements falling into the good, negative, and ambiguous categories are all included in the emotion analysis for mental health. There are several categories of positive psychological elements, each representing a distinct facet of pleasant emotional experiences. These categories include happiness, enthusiasm, cheerfulness, laughing, and smiling [18][19]. Negative psychological aspects include addiction, anxiety, depression, insomnia, stress, and obsessive-compulsive disorder (OCD), according to [20].

Contrarily, ambiguous psychological elements are associated with feelings that are marked by ambiguity and uncertainty in written language, such as "I'm disturbed by my spouse's behaviour and want professional advice on handling anger and depression to save the marriage." Relatives avoid him because of his frequent, unjustified anger, which frequently culminates in verbal and physical outbursts. He clearly battles with socialization, fear, and despair, which are brought on by weariness and a sense of powerlessness". The underlined word in the text, which is about mental health difficulties, conveys a range of feelings. These elements are situation-specific, therefore writings about mental health may not always show one clear emotion but rather a range of emotions depending on the circumstances. Therefore, it is important to deploy LSTM-attention approaches along with additional deeper neural network techniques to identify these emotions in users' writing posted to psychiatrists while taking scenario changes into account. The words are given as categories associated with emotional labels, and their weights correspond to different hidden vectors.

There is great research on text data, the challenge in the text data is to identify the Sarcasm in the text. Sarcasm is a word which hides the original meaning of the text. It is very difficult to identify the mood of the person. It is one of the texts which takes a person into depression. The main motive of its use is to show the opposite emotion as specified in the text. The presence of sarcasm in the text makes more impact on mental health. Identifying the sarcasm and the moto behind the text requires maximum text information related to that tweet. Authors added a new component to identify the sarcasm. Also, improve the accuracy of mental health detection.

To increase the performance of the Sarcastic tweet level Depression Detection by using the sarcastic information available in the tweet, a novel model used called Sarcastic News Dataset and Tweet-based Depression Detection (SNTDD) developed. The preprocessing means removing the noise from the text, which is done on the news headline dataset and Twitter dataset. Then the data is collected into the positive and negative sets based on the sarcastic news dataset. The SNTDD model performs better than the machine learning and Deep Learning model. Additionally, it uses the tweet data to identify the sarcastic tweet and test the model which is trained on the news headline dataset. The proposed model is constructed on the two types of data Twitter and News Headline Datasets which were collected in Jan 2023 and in April 2023 respectively. To augment the overall performance of the SNTDD model employs hybridization of LSTM and CNN. It is used to measure stress through utilizing tweets. The news headline data is used to train the model.

2. Objectives

The Sarcastic News Dataset and Tweet-based Depression Detection (SNTDD) model was designed to have sarcastic phrases which were seen in the tweets being used to detect depression.

Increase the F1 score of the SNTDD model.

In order to determine the sarcasm, the SNTDD model dataset was gathered in February 2023.

3. Models

The Sarcastic News Dataset and Tweet-based Depression Detection (SNTDD) model has a goal of coming up with a classifier that makes use of sarcastic data to enhance stress detection from tweets. Its main goal is to devise a model of integrating sarcasm detection approaches into stress recognition algorithms, and therefore enhancing the effectiveness of text data for stressing identification tasks.

3.1 Problem Formulation

The suggested model for Sarcastic News Dataset and Tweet-Based Depression Detection is illustrated in Figure 1. The SNTDD model uses news dataset in training diagnostic tasks that detect sarcasm. This model recognize anger through the lens of depression. In detecting sarcasm, it is possible to rely on the statistics of the Twitter dataset and compare them with the statistics of the trained sarcasm. The generated data is pre-processed, and the training data is split into three categories: positive, negative, and neutral. The text is labelled as 1, -1, and 0. In the Twitter dataset, the text is labelled as 1 for positive and 0 for negative. In this model, we will take tweets and find sarcastic phrases inside them. The sentiment behind the sarcastic statement has a different significance in the words. To make the prediction, the contrast vectors are sarcastically processed.

The model is described in depth in Section 3.3. The study [44] offered the Finding the Sarcasm_State value. Building on the concept of illicit sarcasm, the work yields an extra value known as Sarcasm_state. The resulting number is used to communicate the sarcasm expressed in the tweet's text. Sarcastic computation is modified in this study to represent the discrepancy between the polarity of nonverbal signals and the polarization of textual content such as words and hashtags. When there is a mismatch between the polarity of the majority of words and the polarity of the majority of hashtags in the tweet's text part, the Sarcasm_state is usually assigned the value 1. Furthermore, when there is a mismatch between the polarity of the majority of words in a tweet's text content and the polarity of the majority of nonverbal emotions, such as emoticons and emojis, the Sarcasm_state is set to 1. Similarly, when there is a mismatch between the polarity of most hashtags and most nonverbals, the Sarcasm_state is set to one. In any other case where the majority of the written and nonverbal parts share comparable polarity.

3.2 Proposed Mathematical Model

Problem Description Identify an unlabeled text t that analyzes its Sarcasm state Ss given by the function F and accepts this text. Thus, such a function generates a label l for a tweet with l ∈ {0,1} the class label of the stressing in the tweet. The training data is applied to calculate the function F parameters, which have larger likelihood losses for the sarcastic tweets, Sst = 1, while having smaller log-likelihood losses for the non-sarcastic tweets with Sst = 0. F∅ $D \rightarrow$ L defines the function F such that L is the class label set. The classifier F uses the data coming from Sarcasm_state to predict which category l the unlabeled tweet ut falls into:

Problem Description The issue at hand is finding a function F such that given any unlabelled text t, it can determine its Sarcasm state Ss. This function should assign a tweet a label l, where l∈{0,1}, which is a classifier used to measure the level of stress in a tweet. The training samples are employed to compute the values of F function wherein for Sst = 0 sarcastic tweets and Sst = 1 non-sarcastic tweets, the likelihood losses are increased and log-likelihood losses are reduced, respectively. F∅ $D \rightarrow$ L explains the function F in which L represents the class labels.

The SNTDD model with a basis on sarcasm discusses the proposed model in detail, starting with the initial preprocessing of the sarcastic text up until the prediction phase. Finally, the concept and operational framework of the proposed Sarcastic News Dataset and Tweet-based Depression Detection model. Lastly, dimension reduction strategies are considered to enhance the functionality of the proposed Sarcastic News Dataset and Tweet-based Depression Detection (SNTDD) model. The cleaning process must be done after collecting the tweets to remove noise and insufficient information. Removing all the tweets with no textual content in the process is the first step done in the cleanup of data.

Furthermore, the rationale and the operational architecture of the SNTDD model are detailed and explained as well. Lastly, the approaches towards dimensionality reduction are elaborated in order to decrease the distortions in the proposed SNTDD model.

3.3 Proposed System Architecture:

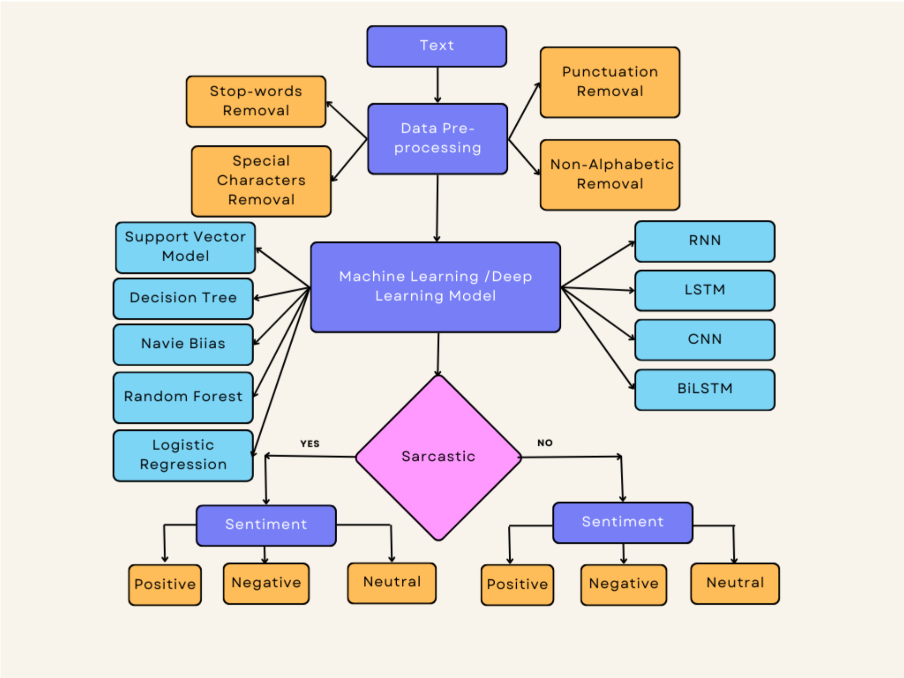

Figure 1. Framework of Proposed SNTDD model.

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Figure 1 depicts the model that was used to identify depression symptoms in sarcastic headlines and tweets. This methodology will most likely include preprocessing text data, extracting relevant attributes, categorizing data using Deep Learning and Machine Learning techniques, and evaluating model performance. The methodology seeks to find language patterns suggestive of sadness and sarcasm using data from social media platforms such as Twitter and news headlines from news sources, thereby advancing mental health research and intervention techniques.

- **Text Data:** News headline data is composed of textual information obtained from news articles on a number of topics, including current events, politics, business, sports, and entertainment. It is valuable for a range of natural language processing applications, including as sentiment analysis, topic modelling, and trend detection, because it informs, impacts, and reflects public sentiment. Analysing news headline data provides insights into current events, emerging trends, and public opinion, despite its dynamic nature and potential downsides such as bias and noise.

Data Preprocessing: Refers to news headlines; that is, text, extracted from a given number of stories on various topics because news today can contain anything-related current affairs, political issues, business, sports, and entertaining stories. Many machine learning applications, such as sentiment analysis, topic modeling, and trend detection, are benefited from the characteristic of news headline data of reflecting, changing, and educating public opinion.

It may be dynamic, however, with biases and noise but it can offer insights regarding public opinion, developing trends, and current events.

Data can be prepared using any one of the following data preparation techniques**:**

Data cleaning:

is the process of ensuring information correctness through removal or correction of errors, filling missing values, and outliers.

Data Transformation:

includes transforming categorical data into numeric form, applying the log transformation to remove skewness, and scaling or normalizing numeric attributes so that they become comparable to one another.

Feature Engineering:

is the process of making new features from existing ones. Examples include converting text data into numerical representations, extracting time or date features, and polynomial features.

Feature Extraction:

Feature selection and other techniques, like Principal Component Analysis (PCA), are used to reduce the number of features so as to decrease the complexity of the model and improve its performance.

Resampling Techniques such as oversampling or under-sampling, are used to address class imbalance in classification problems.

Data Splitting is the process of separating data into testing, validation, and training sets to evaluate model performance.

Stop Word Removal removes unnecessary terms like "the," "is," and "and" from the text to improve model comprehension.

- **Deep Learning Model and Machine Learning Model**

Usually, Deep Learning and Machine Learning models utilize pre-processed data as input. For the purpose of training and testing deep neural network or machine learning model's, unprocessed information must first undergo preprocessing procedures that clean, modify, and arrange it.
Making ensuring the data is in a format the model can comprehend and use for learning is known as preprocessing. Through activities like noise removal, managing missing data, scaling of features, and category encoding, it contributes to the enhancement of the model's performance, accuracy, and generalizability.
Generally, the pre-processed data for supervised training tasks involves features (input variables) and combining labels (output variables). It could just include features for unsupervised learning tasks. No matter what the particular task is, the processed data's quality greatly.

- **Sarcastic**

To identify sarcasm in text using ML or DL approaches, preprocess text data by cleaning, tokenizing, and converting it into numerical representations. Train models such as traditional ML classifiers or deep learning architectures like RNNs or Transformers on the pre-processed data, evaluating their performance using metrics like accuracy and F1-score. Iterate on model selection, preprocessing techniques, and hyperparameter tuning to optimize performance for sarcasm identification in text. Top of Form Two categories sarcastic and non-sarcastic are used to categorize the text.

- **Sentiment**

Determine whether all three sorts of comments were sarcastic or not, and if they're positive, negative, or neutral.

- **Sarcasm state value and the sentiment**

Calculate the amount of Sarcasm_State. Expanding on the concept of illicit sarcasm, the work [44][45] provides Sarcasm_state, an extra value. The resulting number is used to communicate the sarcasm expressed in the tweet's text. Sarcastic computation is modified in this study to represent the discrepancy between the polarity of nonverbal signals and the polarization of textual content such as words and hashtags. When there is a mismatch between the polarity of the majority of words and the polarity of the majority of hashtags in the tweet's text part, the Sarcasm_state is usually assigned the value 1. Furthermore, the Sarcasm_state is assigned a value of 1 when the polarity of most words in a tweet's text differs from the orientation of most nonverbal emotions, such as emoticons and emoji. Similarly, the Sarcasm_state is set to 1 when the majority of word polarization and all nonverbal polarity diverge. In any other case where the majority of the written and nonverbal parts share comparable polarity.

- **Abbrevations and Pseudocode:**

Input: News Headlines Dataset in the set D. The labelled Training data set of news headlines.
Output: Sarcasm detection si
S🡐 Number of sarcastic statements in the dataset
NS🡐 The number of non-sarcastic sentences in the dataset.
Ps 🡐 The number of positive sarcastic phrases in the dataset.
NegS 🡐 Number of negative-sarcastic statements in the dataset
PNS 🡐 Number of positive non-sarcastic statements in the dataset
NegNS 🡐 Number of negative non-sarcastic statements in the dataset

N🡐Neutral not sarcastic or non-sarcastic but if it is a simple sentence then it has Negative and positive values NP and NN.
Sarcastic and non-sarcastic comments with negative values; combine both and use the Depression detection algorithm to determine the polarity of depression.

Pseudo Code	
if Ps> NegS & S>NS then Sarcasm_Detection 🡐0 else if Ps< NegS & S>NS then Sarcasm_Detection 🡐1 else if NegS> NegNS & S<NegS then Sarcasm_Detection 🡐1 else	if NegS<NegNS & S>NegS then Sarcasm_Detection 🡐1 else if NegS> NegNS & Ps>Pns then Sarcasm_Detection 🡐1 else if NegS< NegNS & Ps>Pns then Sarcasm_Detection 🡐1 else then Sarcasm_Detection 🡐0

- **Proposed Model**

Instruction of the suggested SNTDD model This section discusses the suggested SNTDD model's training process and associated algorithms. This paper presents the concept and operation of the suggested SNTDD model in order to comprehend the loss function and training process. The suggested SNTDD model's guiding idea is to minimize the possibility that a sarcastic tweet would fall under the stress category and maximize the likelihood that a non-sarcastic tweet will meet criteria. This can be understood as decreasing the loss for tweets that aren't sarcastic. It can be observed from the work [46] that, In a logistic regression model, the possibility that a tweet *f* belongs to the class l given every feature vector *f* whose equivalent class label is l.

The following indicates how likely it is that tweet f belongs in class l:

$f(x)l(1 - f(x))(1 - l)$ --(1)

In this case, the logistic function, also known as or the sigmoid is denoted by the symbol P(f).

$f'(x) = 1/(1 + exp(-w.f))$ ---(2)

Thus, in this case, the log-likelihood is as follows:

$llog(p(f)) + (1 - l)log(1 - p(f))$

For non-sarcastic texts $(Nsi = 0)$,

the probability of being a part of the class Depression is increased. Therefore, the possibility of the tweets $f\boldsymbol{i} \in Ds'$ is

$p(f\boldsymbol{i})li(1 - p(f\boldsymbol{i}))1-li$

Then the scenario is given by

$(1 - li)log(1 - p(f\boldsymbol{i})) + li\,log(p(f\boldsymbol{i}))$ ---(3)

For Sarcastic texts *(Si=1)*

the texts $f\boldsymbol{i} \in Ds$ is

$(1 - p(f\boldsymbol{i}))li * p(f\boldsymbol{i})1-li$

Then the scenario is given as

$li \log(1 - p(f\boldsymbol{i})) + (1 - li) \log(p(f\boldsymbol{i}))$ --(4)

The Sarcastic News Dataset and Tweet-based Depression Detection (SNTDD) loss function calculated as:

$f(w)-tl(w)=0$

$f(w)=-[Equation\ (3)+Equation(4)]$

$= \sum_{i=0}^{N}[\ -li \log(1 - p(f\boldsymbol{i}))\ -\ (1 - li) \log(p(f\boldsymbol{i}))\ -(1 - li)\log(1 - p(f\boldsymbol{i}))-\ li \log(p(f\boldsymbol{i}))]$---(5)

3.4 Experimental Setup

The experimental setup, baseline models, and datasets utilized to evaluate the performance of the proposed model are all described in this section. Python is used in all of the experiments.

- **Dataset Description**

Datasets with news headlines and tweets from February 2023 are sourced from Kaggle. To identify the sarcasm, we need sarcastic data, which is present in news headlines. To control the participants' mental health, a Twitter dataset was gathered during the January 2023 trial period. Implementing the model using data collected over multiple time periods validates its validity. Tweets are extracted using Tweepy. "I am very depressed," a hashtag, is used to collect tweets that reflect stress or mental illness. The keywords "depressed" (*ti=1*) are classified once all of the tweets have been collected. The queries "I am not depressed" and "I am very much comfortable" are used to collect the tweets.
"I am not depressed" are used to gather the tweets. Words of this kind are classified as non-depressive (*ti=0*). The pattern-based extraction model is applied here. This type of word is categorized as non-depressive (*ti=0*). Here, the extraction technique based on patterns is used.

- **Comparative Study**

Early/simple models are important because they provide a benchmark for assessing the efficacy of increasingly complicated models.
Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), Logistic Regression (LR), XGboost, and Navie Bias (NB) are the first, most basic, and widely used machine learning models. These models are used to determine how well the suggested model performs. Since those models are primarily utilized for text data and their success in text data classification, that is the rationale for their use. [34][35].
The details of the initial/simple model are as below:

- **Support Vector Machine (SVM)**

Because they can identify the best hyperplane to maximally segregate classes in a dataset, Support Vector Machines (SVM) are popular classifiers in machine learning. SVMs are useful in a variety of classification applications because they maximize the margin between classes in an effort to achieve strong generalization to unknown data. Applications like text classification, picture recognition, and bioinformatics can benefit from their adaptability. When working with high-dimensional data or in scenarios where there are more characteristics than samples, SVMs are especially helpful. SVMs are now the standard solution for many classification issues in both academic research and commercial applications because of their efficacy and strong theoretical underpinnings.

- **Logistic Regression (LR)**

Based on the observable properties of the input data, Naïve Bayes (NB) is a popular binary classification technique that computes posterior probability for each class label. Its foundation is the Bayes theorem. Assuming class-conditional independence among input features, Naïve Bayes streamlines the computation by considering each feature as independent of the others. Although this assumption is sometimes oversimplified in practical circumstances, it enables Naïve Bayes to function successfully and efficiently, particularly if there is a shortage of training data or processing resources. Naïve Bayes has shown to be exceptionally robust despite its simplifying assumptions, and it is widely used in a variety of fields, including text categorization, spam filtering, and medical diagnosis.

- **XGboost**

XGBoost is a Machine Learning model that is very effective and scalable. It works well for supervised learning tasks, especially when dealing with structured data. It is part of the ensemble learning group and uses gradient boosting models as its foundation. It iteratively constructs a weak learner ensemble, finding the most fitted theory by optimizing a function that is objective. Proven for its efficiency, scalability, and internal handling of missing variables, XGBoost finds extensive application in a variety of fields, such as e-commerce, healthcare, and finance.

- **Decision Tree (DT)**

Decision trees are straightforward yet effective machine learning models that divide information recursively according to attributes in order to forecast target variables. This makes decision trees easy to comprehend and analyze. Nevertheless, when dealing with complex data sets, they may over fitting, which is why ensemble techniques were created to improve.

- **Random Forest (RF)**

Random forest training is a collaborative learning approach that may be applied to tasks such as classification and regression. It constructs several decision trees and then adds up their predictions to increase accuracy and robustness. Random Forest is a commonly utilized technique in various fields since it decreases overfitting and improves the accuracy of generalization through combining the forecasts of many different trees.

- **Navie Bias (NB)**

Basing its probabilistic classifier on the assumption of features independence and the theorem of Bayes, Naive Bayes is a straightforward but powerful algorithm. Naive Bayes, despite its simplicity, excels in a variety of classification tasks because of its computational efficiency and capacity to handle high-dimensional data, especially in categorization of texts and spam filtering. The Sarcastic News Dataset and Tweet-based Depression Detection (SNTDD) model that has been suggested and all of these baseline classifiers are applied to the all datasets used here.

3.5 Performace Measuers

The most widely used performance metrics are recall, F1 score, Accuracy, and Precision. The Accuracy and F1 score calculated for the suggested model's efficiency. By comparing the expected data with the entire dataset utilized for testing, the Accuracy can be determined [47]. Based on their computations of True Positive *(TP*), False Positive *(FP),* True Negative *(TN)* and False Negative *(FN)* the forecasts are divided into groups. Next, the Accuracy is calculated with the following equation:

Accuracy=(TP+TN+FP+FN)/(TP+TN) --(6)

The harmonic mean of precision *(P)* and recall *(R),* where recall is the ratio of all actual positive samples to the number of correct positive predictions and precision is the ratio of all correct positive assumptions to all positive predictions, is employed for calculating the F1-Score, a measure of a model's accuracy [48][49]. Because of its accuracy and recall balance, the F1-Score is a useful measure for evaluating models in binary classification tasks, especially when there is a disparity between the classes.

*F1 Score= 2(P*R)/(P+R)* ---(7)

about the studies carried out with the datasets employed here.

4. Results and Discussions

The results and their analysis of the experiments carried out in this study are presented in this part. The proposed model was evaluated on twitter dataset, news headline dataset, sarcastic and non-sarcastic dataset, and compared with Support Vector Classifier (SVC) [49], Linear Regression (LR) [11], Decision Tree (DT) [11], Naïve Bias (NB) [49], and Random Forest (RF) [47]. The ability to classify textual data is commonly acknowledged.

4.1 Preprocessing results

To provide train and test datasets for machine learning models, which are required for preprocessing in Natural Language Processing (NLP) in order to train and evaluate them. A sizable portion of the data needed to train the model on various language patterns and characteristics is typically present in the train dataset. To evaluate the model's performance with unknown data, on the other hand, the test dataset serves as a stand-alone set. Preprocessing models like as feature extraction, cleaning, and tokenization are applied similarly to both datasets to ensure consistency and dependability. Determining the model's generalization ability and preventing overfitting depend on the train-test split. We preprocess the tweeter dataset for this model. Following preprocessing, we label the datasets to segregate them.

The dataset from Twitter that has a label of either 0 or 1. This binary labeling technique probably denotes distinct classes or categories, with positive tweets being labeled as 0 and negative posts as 1. This makes it easier to train and assess deep learning or machine learning models to recognize negative sentiment and positive sentiment, respectively.

7.2 Evaluation of Proposed SNTDD Model

We analyzed Twitter and news headlines datasets in our research using a variety of deep learning as well as machine learning models, including neural networks, Support vector classifier (SVC), Decision Tree (DT), Random Forest (RF), Naïve Bayes (NB) and Linear Regression (LR). We used the linguistic cues associated with negativity and sarcasm to construct models for recogni zing underlying mental disorders or feelings of sadness in people. Using this incorporated dataset, ou r objective is to detect mental disorders using text. By using an interdisciplinary approach, we were able to use insights from the news and social media domains to better understand mental health and well-being through textual analysis.

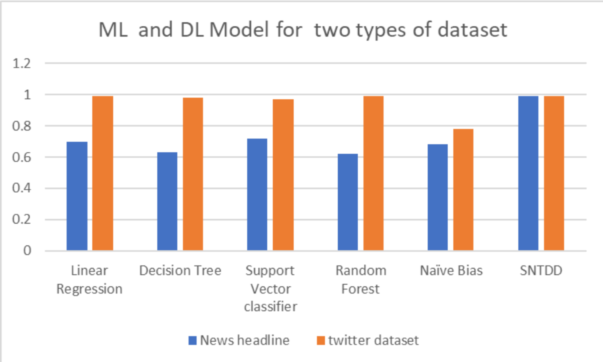

Figure 7. Deep Learning model and Machine Learning model accuracy for both datasets.

The accuracy of deep learning (DL) model and the accuracy of machine learning (ML) models applied to the news headline and Tweet datasets is shown in Figure 6. The accuracy scores and other performance parameters of multiple ML and DL algorithms on each dataset are probably depicted in this image, which sheds light on the relative merits of various modelling strategies for textual data analysis. Researchers can assess the relative advantages and disadvantages of each model for capturing the subtleties of language and sentiment seen in news headlines and Twitter data by contrasting the accuracy of ML and DL models across the two datasets.

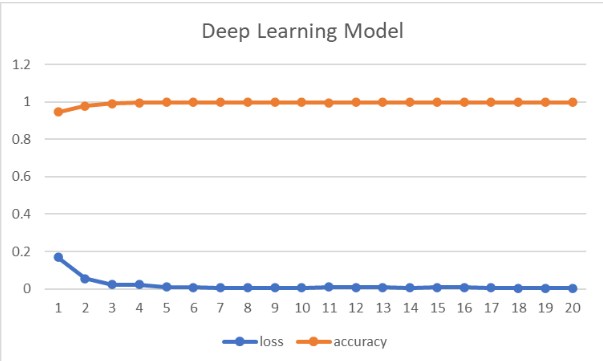

Figure 8. Deep Learning model loss and Accuracy calculated for 20 epoch.

Figure 8 represents the performance of the neural network model over a period of 20 epochs, showing an enormous increase in correctness and an associated decrease in loss. The pattern indicates that the accuracy and loss values decrease steadily with each epoch, indicating an important increase in the model's prediction abilities. The model effectively learns and generalizes patterns from the training data, as evidenced by its remarkable 99% accuracy by the 20th epoch. Furthermore, the model is exhibiting a tendency to approach optimal performance as indicated by the decreasing loss values, which also show that the model is highly efficient in reducing prediction errors throughout multiple epochs. Figure 9 represents the model test and train accuracy for 3 epochs. Firgure 10 represents the model test and train loss for 3 epochs.

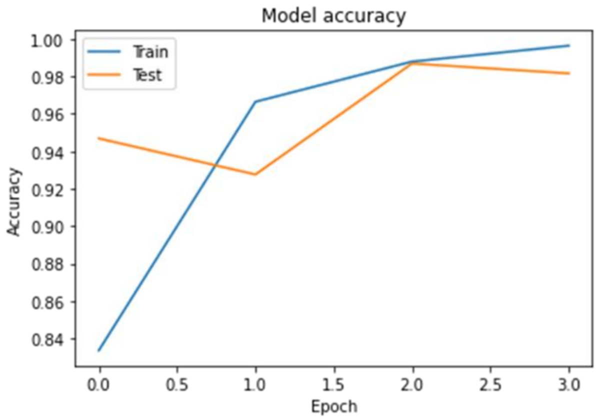

Figure 9. Train and Test Model Accuracy calculated for 3 epoch.

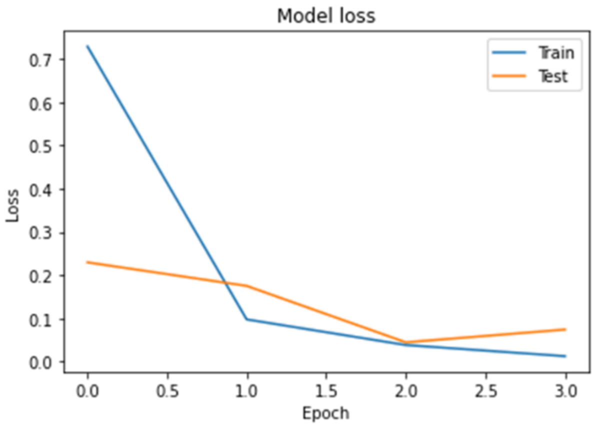

Figure 10. Train and Test Model Loss calculated for 3 epoch.

5. Conclusion and Future Work

The Many researchers worked on media-based depression detection. This study presents the construction of a novel Sarcastic News Dataset and Tweet-based Depression Detection (SNTDD) classifier to extract sarcastic contents information and identify stress at the tweet level. The SNTDD model's basic goal is to minimize loss and maximize the accuracy for sarcastic tweets while minimizing loss for non-sarcastic. The model gets an improved accuracy of 97.4 % as compared to the deep learning algorithms and machine learning algorithms for the two distinct datasets, the tweet and news headline datasets, as well as the combined negative and sarcastic data are used in the tests. Also, we have achieved a F1-score of 94.4.

The development of multi-task learning models to use the hints from related categorization tasks in the diagnosis of clinical depression is the future direction of this work.

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