**Table 2.1: Comparison of selected research work on suicidal ideation based on ML**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **PAPER TITLE [ID]** | **AUTHORS (YEAR)** | **OBJECTIVE** | **LIMITATIONS** | **TECHNIQUES** | **FEATURES** | **DATASET** | **REPORTED RESULT** |
| An across |  |  | not using network embedding techniques and Deep Learning techniques. It does not handle fake profiles. | Random forest (RF), Bayes Net (BN),  SVM, Decision Tree  (DT) and Adaboost (AdaB). Tuser algorithm is also used to search for their matched profiles in Twitter. |  |  |  |
| online |  | automatical |  |  |  |
| social |  | ly detects |  |  |  |
| networks |  | suicidal | Emotional |  |  |
| profile |  | users | features, |  |  |
| building  approach:  Applicati | Mbarek et al (2022) | through  their  created | Stylometric  features, Temporal  features, Timeline | Twitter (TM),  YouTube (YT),  Tumblr (TM) | F1-score: 85.4% |
| on to |  | profiles in | features, Account |  |  |
| suicidal |  | Online | features |  |  |
| ideation |  | Social |  |  |  |
| detection |  | Networks. |  |  |  |
| [7] |  |  |  |  |  |
| Bootstrap |  | automatical | This system will not be able to detect suicidal users in social networks in other languages | SVM classifier (using  the features BoW,  BoW+Embedd ings, Tf/Idf, and Tf/Idf + Embeddings) and Rasa (with default features extraction system) |  | Life corpus, Reddit corpus, Department of Criminal Justices |  |
| ping |  | ly detect |  |  |
| semi- |  | and classify |  |  |
| supervise |  | texts |  |  |
| d  annotatio n method for | RWA  Caicedo et al (2022) | collected  from social media related to | Bag of Words  (BoW) features, Lexical & Syntactical features | Macro F1- score: 0.78–  0.81 |
| potential |  | suicide and |  |  |
| suicidal |  | depression- |  |  |
| messages |  | based |  |  |
| [8] |  | samples. |  |  |

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **PAPER TITLE [ID]** | **AUTHORS (YEAR)** | **OBJECTIVE** | **LIMITATIONS** | **TECHNIQUES** | **FEATURES** | **DATASET** | **REPORTED RESULT** |
|  |  |  |  | NLTK, |  |  |  |
|  |  |  |  | Random |  |  |  |
|  |  |  |  | Forrest (RF), |  |  |  |
|  |  |  |  | Support |  |  |  |
|  |  |  |  | Vector |  |  |  |
|  |  |  |  | Machine(SVM |  |  |  |
|  |  |  |  | ), Stochastic |  |  |  |
|  |  |  |  | Gradient |  |  |  |
|  |  |  |  | Descent |  |  |  |
|  |  |  |  | classifier |  |  |  |
|  |  |  |  | (SGD), |  |  |  |
|  |  |  |  | Logistic |  |  |  |
| A  Comparat ive Analysis on Suicidal Ideation Detection Using NLP,  Machine, and Deep Learning [9] | Haque et al (2022) | To identify suicidal thoughts from the social media platform Twitter | improve the model's performance and produce a practical online application for clinical psychologists and healthcare practitioners | Regression  (LR), and Multinomial Naive Bayes (MNB), Long-  Short Term Memory (LSTM), Bi-  directional LSTM (BI-  LSTM), Gated Recurrent Unit (GRU), Bi-  directional GRU (BIGRU), | Sentimental, Emotional, n-gram Features | Twitter subreddit “SuicideWatch” (SW) | F1 score: 0.93 |
|  |  |  |  | combined |  |  |  |
|  |  |  |  | model of CNN |  |  |  |
|  |  |  |  | and LSTM (C- |  |  |  |
|  |  |  |  | LSTM), Keras, |  |  |  |
|  |  |  |  | Tweepy API, |  |  |  |
|  |  |  |  | VADER, |  |  |  |
|  |  |  |  | TextBlob, |  |  |  |
|  |  |  |  | CountVectoriz |  |  |  |
|  |  |  |  | er and word |  |  |  |
|  |  |  |  | embeddings. |  |  |  |

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **PAPER TITLE [ID]** | **AUTHORS (YEAR)** | **OBJECTIVE** | **LIMITATIONS** | **TECHNIQUES** | **FEATURES** | **DATASET** | **REPORTED RESULT** |
|  |  | classifying suicide notes collected from social media. | collect more | Linguistic Inquiry and Word Count software  (LIWC 2015).  Techniques used: J48, Naive Bayes, Bayes Net, LMT, CNN, Bi-LSTM, Bi-  LSTMAttentio n, DLSTMAttenti on, Transformer |  |  |  |
|  |  | precise data |  |  |  |
|  |  | from |  |  |  |
|  |  | different |  |  |  |
| Automati c identificat ion of suicide notes with a transform er-based deep learning model [10] | Zhang et al (2021) | social media  and groups of  people. Semi- supervised and unsupervise d approaches are not used.  It is not directly interpretable so not suitable for | linguistic and psychological features | Kaggle's Suicide Notes | F1-score: 94.9% |
|  |  | clinical |  |  |  |
|  |  | decision- |  |  |  |
|  |  | making |  |  |  |
|  |  | process |  |  |  |
|  |  | This paper |  | J48, |  |  |  |
| Machine |  | analyzes |  | LogitBoost, |  |  |  |
| Learning- |  | Reddit | Other social | Naïve Bayes, |  |  |  |
| Based |  | posts to | media texts | Random |  |  |  |
| Social |  | identify | are not | Forest, |  |  |  |
| Media  Analysis for | Gupta et al (2021) | users who  are on the verge of | implemented  , Deep Learning | Sequential  Minimal Optimization | Sentimental, Emotional Features | Reddit C-SSRS Suicide Dataset | Precision: 71.40% |
| Suicide |  | inflicting | techniques | (SMO), |  |  |  |
| Risk |  | self-harm | are not | Support |  |  |  |
| Assessme |  | or | explored | Vector |  |  |  |
| nt [11] |  | committing |  | Machine |  |  |  |
|  |  | suicide. |  | (SVM) |  |  |  |

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **PAPER TITLE [ID]** | **AUTHORS (YEAR)** | **OBJECTIVE** | **LIMITATIONS** | **TECHNIQUES** | **FEATURES** | **DATASET** | **REPORTED RESULT** |
|  |  | automatical ly identify suicide notes from other types of social media and clasify them | This paper |  |  |  |  |
|  |  | does not |  |  |  |  |
|  |  | follow |  |  |  |  |
|  |  | linguistic |  |  |  |  |
|  |  | patterns on |  |  |  |  |
| Hierarchi |  | these type of |  |  |  |  |
| cal |  | textual data |  |  |  |  |
| Multiscal  e Recurrent Neural Networks for Detecting Suicide | Schoene et al (2021) | so the  accurate classification is not possible here. In future these linguistic | RNNs, Dilated LSTM,  Maximum Entropy, Bi- LSTM | Linguisitc, Sentimental, Emotional features | Texas Department of Criminal Justices (2019) , Tumbler(2013): Suicide notes, blogger.com | F1-score: 96.10%(Experi ment-2)  F1-score: 88.26%(Experi ment-1) |
| Notes |  | differences |  |  |  |  |
| [12] |  | could be |  |  |  |  |
|  |  | helpful for |  |  |  |  |
|  |  | analysis of |  |  |  |  |
|  |  | mental |  |  |  |  |
|  |  | health issues |  |  |  |  |
|  |  | online. |  |  |  |  |
|  |  | The | the proposed model is a black box because the inner decision process of neural networks is too complex to be translated into transparent rules. |  |  |  | F-score: 0.870(KARA)  F-score: 0.791(Bi- LSTM) |
|  |  | objective of |  |  |  |
|  |  | this study |  |  |  |
|  |  | is to |  |  |  |
|  |  | develop a |  |  |  |
|  |  | domain |  |  |  |
| Detecting |  | knowledge |  |  |  |
| suicide |  | -aware risk |  |  | 5682 Cantonese |
| risk using |  | assessment |  |  | conversations |
| knowledg |  | (KARA) |  |  | between help- |
| e-aware |  | model to |  |  | seekers and |
| natural  language | Xu et al  (2021) | improve  our ability | KARA,Bi-  LSTM,MLP | semantic | counselors. Of  those 682 |
| processin |  | of suicide |  |  | conversations |
| g and |  | detection in |  |  | disclosed crisis |
| counselin |  | online |  |  | intentions of |
| g service |  | counseling |  |  | suicide. |
| data [13] |  | systems. |  |  |  |

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **PAPER TITLE [ID]** | **AUTHORS (YEAR)** | **OBJECTIVE** | **LIMITATIONS** | **TECHNIQUES** | **FEATURES** | **DATASET** | **REPORTED RESULT** |
| Suicidal |  | to analyse the data from online social media mainly twitter and detect suicide ideation |  | Logistic regression, NB, RANDOM FOREST,  XGBoost |  |  |  |
| ideation |  | The paper |  |  |  |
| predictio |  | uses small |  |  |  |
| n in |  | dataset for |  |  |  |
| twitter  data  using | kumar et al(2020) | their  experiment  thats way | TF-  IDF,LIWC,stastical  feature | TWITTER | F-score: 0.99(RF) |
| Machine |  | they get that |  |  |  |
| Learning |  | amount of |  |  |  |
| technique |  | accuracy |  |  |  |
| s [14] |  |  |  |  |  |
|  |  | In this |  | 98 terms related to suicide were collected from online, academic, and other sources.  Mental health professionals and members of the electronic mailing list of the American Association of Suicidology were asked to validate terms. |  | Internet-based resources such as blogs. message boards. news sites. |  |
|  |  | paper they |  |  |  |
|  |  | find What | The lexicon |  |  |
| Social |  | terms are | did not |  |  |
| Media |  | commonly | capture |  |  |
| and |  | used when | international |  | The survey |
| Suicide: |  | people | phrases. It |  | validated |
| A  Validatio n of | Parrott et al (2020) | communica  te about suicide and | also  did not document | sampling  approaches emailing practicing | common  terms used to communicate |
| Terms to |  | phrases | less direct |  | about |
| Help |  | from the | language, |  | suicide. |
| Identify |  | American | such as |  |  |
| [15] |  | English | expressions |  |  |
|  |  | language | of emotion. |  |  |
|  |  | were |  |  |  |
|  |  | compiled. |  |  |  |

|  |  |  |  |  |  |  |  |
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| **PAPER TITLE [ID]** | **AUTHORS (YEAR)** | **OBJECTIVE** | **LIMITATIONS** | **TECHNIQUES** | **FEATURES** | **DATASET** | **REPORTED RESULT** |
| Assessme |  | The objective of this project is to detect the suicide indication from the received texts form several social networks. | A limitation in this research is that, because it is oriented to computer science, we do not delve into the area of psychology, which is addressed in other research related to the Life research platform. | 28 supervised classifier algorithms. Life Corpus developed by the research group from Natural Language Processing and Information Systems, ascribed to the University of Alicante. | Bag of Words (WORD) Bag of Stems (STEM) Bag of Lemmas (LEMMA) Bag of SYNSETS  (SYNSET) Bag of POS (POS) | A bilingual corpus (English and Spanish) oriented to suicide. Texts from several social networks like Twitter,Weibo and Netlog. |  |
| nt of |  |  |
| supervise |  |  |
| d |  |  |
| classifiers | R.W. |  |
| for the  task of detecting | Acuna  Caicedo et al | F-score: 0.7148. |
| messages | (2020) |  |
| with |  |  |
| suicidal |  |  |
| ideation |  |  |
| [16] |  |  |
|  |  | Used to automatical ly distinguish Suicidal and Non- Suicidal tweets.. | The | WEKA tool, Naïve Bayes (NB),  Multinomial Naïve Bayes (MNB), ZaroR,  Decision tree (REPTree and J48), Logistic Regression (LR), SMO  and Support Vector Machine (SVM) |  | Twitter Application Programming Interface (API) |  |
|  |  | connectivity |  |  |
| Detection |  | between |  |  |
| of |  | suicidal |  |  |
| Suicidal |  | users is not |  |  |
| Ideation |  | explored, |  |  |
| on |  | Blog posts |  |  |
| Twitter  using Machine | S.T.Raban  i et al (2020) | will be  investigated later, | TFIDF  BoW Manual Features | Accuracy: 98.5% |
| Learning |  | Multi-class |  |  |
| & |  | classification |  |  |
| Ensemble |  | is not used, |  |  |
| Approach |  | Deep |  |  |
| es [17] |  | Learning |  |  |
|  |  | algorithms |  |  |
|  |  | are not used |  |  |
| Recognizi |  | It focuses on developing an effective diagnostic tool for depression who demonstrat e the need for  clinical treatment. | the nature of VPA-DR  conversation initiation technique. | VPA-DR,  Dialogflow Machine Learning (ML) & SVM |  |  |  |
| ng |  |  |  |  |
| Suicidal |  |  |  |  |
| Intent in |  |  |  |  |
| Depresse |  |  |  |  |
| d  Populatio | Hassan et  al(2020) | Emotional feature | Kaggle dataset | Accuracy:  76% |
| n using |  |  |  |  |
| NLP: A |  |  |  |  |
| Pilot |  |  |  |  |
| Study |  |  |  |  |
| [18] |  |  |  |  |

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **PAPER TITLE [ID]** | **AUTHORS (YEAR)** | **OBJECTIVE** | **LIMITATIONS** | **TECHNIQUES** | **FEATURES** | **DATASET** | **REPORTED RESULT** |
| Question |  |  | The error |  |  |  |  |
| Answerin |  | To | margin a |  |  |  | The suicide |
| g for |  | determine | predicted |  |  |  | idendicator |
| Suicide  Risk Assessme nt | Alambo et al(2019) | suicidal  intend by asking them some | Reddit post’s  suicide risk severity level differs | SNOMED, ICD, UMLS,  and DataMed | Semantic features | Reddit, Manual depressed disorder people | performed  well in this papper however the |
| using |  | designed | from the |  |  |  | neumeric data |
| Reddit |  | question | annotator’s |  |  |  | is not given |
| [19] |  |  | label. |  |  |  |  |
| An Unsuperv ised Learning Approach for  Automati cally to Categoriz e Potential Suicide Messages in Social Media [20] | Parraga- Alava et al (2019) | objective is to categorize suicide messages collected from social media which is based on unsupervis ed learning. | in future the authors should use more robust similarity metrics and clustering algorithm to improve match rates.  And use more texts | NLTK  (Natural Language Toolkit),"tm" libraries, k- means, Partitioning Around Medoids (PAM),  Hierarchical clustering | semantic features | Life Corpus | F1-score: 87% |
| Extractin |  |  |  |  |  |  |  |
| g |  |  |  |  |  |  |  |
| psychiatri |  |  |  |  |  |  |  |
| c  stressors for suicide from social media using | Du et al (2018) | To detect early prevention of suicidal behaviors and suicide. | Highly imbalanced dataset,lack data for exact mental health status | Extra Trees  (ET),  Random Forest (RF), Logistics Regression (LR) and (SVM) | linguistic, lexical, syntactic,  n-grams, | Twitter, Social media,Mental health status | F1-score: 83%, |
| Deep |  |  |  |  |  |  |  |
| Learning |  |  |  |  |  |  |  |
| [21] |  |  |  |  |  |  |  |

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **PAPER TITLE [ID]** | **AUTHORS (YEAR)** | **OBJECTIVE** | **LIMITATIONS** | **TECHNIQUES** | **FEATURES** | **DATASET** | **REPORTED RESULT** |
| Detection of Suicide- Related Posts in Twitter Data Streams [22] | Vioulès et al(2018) | Social media platform Twitter to quantify suicide- warning signs for  individuals and to detect posts containing suicide- related content. | the results of the full methodology run on  only two Twitter users. | multinomial Naïve Bayes, Sequential Minimal Optimization (SMO) with a poly kernel,  C4.5  decision tree (J48), nearest neighbor classifier (IB1), multinomial logistic regression, rule  induction (Jrip), Random Forest, SMO with a Pearson VII universal kernel function (PUK). | n-grams, symptoms, pronouns, and swear components.andbe havioral | twitter | F1-score: 0.334 |
| Validatin g Machine Learning Algorith ms for Twitter Data Against  Establishe d Measures of Suicidalit y [23] | Braithwai te et al (2016) | The objective of this study is to validate the use of Machine Learning algorithms for Twitter data against empirically validated measures of suicidality in the US population. | This study has a number of limitations as well as strengths.No vel research ideas are often tested.  The results provide strong evidence i.e. reliably able to differentiate those  who are clinically significantly suicidal from those who are not. | Tree Learning Algorithm | Internet-Based Profile and Linguistic | social media; twitter | Accuracy: 92% |

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **PAPER TITLE [ID]** | **AUTHORS (YEAR)** | **OBJECTIVE** | **LIMITATIONS** | **TECHNIQUES** | **FEATURES** | **DATASET** | **REPORTED RESULT** |
| Detecting Suicidalit y on Twitter [24] | O'Dea et al (2015) | To design and implement an automated computer classifier that could replicate the accuracy of the human coders using recall and precision metrics. | unclear whether the ‘strongly  concerning’ tweets were genuine statements of suicidality. | SVM, Logistic Regression | Statistical analysis & Semantic features | twitter | Accuracy: 76% |
| A Hybrid system for emotion extraction from suicide notes [25] | Nikfarjam et al(2012) | present a method for sentiment analysis of suicide notes submitted to the  i2b2/VA/Ci ncinnati Shared Task 2011. | the rules were  not enough to cover the test cases for some emotion categories (hopefulness, blame, anger and abuse) which caused their result to become zero. | rule-based engine and trained a Support Vector Machine (SVM) | syntactic, clausal, TF-IDF and semantic features | suicide notes (around 600 training notes and 300 test notes) | F-score: 47.50% |
| Three Hybrid Classifier s for the Detection of Emotions in suicide notes [26] | Liakata et al (2012) | The objective of this study is to creating a system able to detect emotions in suicide notes. | A drawback in using SVMs is that one cannot easily model the sequence of categories in a message with-  out introducing errors. | JRip and SMO  &LibSVM and CRFSuite, | content-based  ,structural,ngram and unigram | social media; twitter; | F1-score: 45.6% |

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **PAPER TITLE [ID]** | **AUTHORS (YEAR)** | **OBJECTIVE** | **LIMITATIONS** | **TECHNIQUES** | **FEATURES** | **DATASET** | **REPORTED RESULT** |
| Suicide Note Sentiment Classifica tion: A Supervise d Approach Augment ed by Web Data [27] | Xu et al (2012) | To create a sentiment classificatio n system for the Fifth i2b2/VA Challenge Track 2, which can identify thirteen subjective categories and two objective categories. | No-label sentences are labeled& Multiple labels compete with each other. | linear SVM,POS  patterns, | Computing and ranking , selection through LiveJournal corpus | Suicide note, spanning n- gram, web data | F-score: 0.59. |
| A Hybrid Approach to Sentiment Sentence Classifica tion in Suicide Notes [28] | Sohn et al(2012) | This paper describes the sentiment classificatio n system.  Challenge.  The sentiment classificatio n task is to assign any pertinent emotion to each sentence in suicide notes. | The major advantage we observed was that it generalized well across the problem space, when provided with sufficient training data. | MNB, RIPPER,  Token normalization, Classifier Ensemble, Corpus re- annotation, GENIA  tagger, SVM | sentiment classification | The training set consists of 600 actual suicide notes and the gold standard annotation of the emotional sentences. | F-score: 0.5640. |

Table 2.2: Year wise count of selected research papers on Machine Learning

|  |  |
| --- | --- |
| **Year** | **No of papers** |
| 2022 | 3 |
| 2021 | 4 |
| 2020 | 5 |
| 2019 | 2 |
| 2018 | 2 |
| 2016 | 1 |
| 2015 | 1 |
| 2012 | 4 |
| Total = | 22 |

**Table 2.3: Comparison of selected research work on suicidal ideation based on DL**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **PAPER TITLE [ID]** | **AUTHORS (YEAR)** | **OBJECTIVE** | **LIMITATIONS** | **TECHNIQUES** | **FEATURES** | **DATASET** | **REPORTED RESULT** |
|  |  | Early |  |  |  |  |  |
|  |  | detection |  |  |  |  |  |
| Detection |  | of suicide |  |  |  |  |  |
| of Suicide |  | ideation |  |  |  |  |  |
| Ideation in  Social Media Forums Using Deep | Tadesse et al (2020) | through  Deep Learning and Machine Learning | Data deficiency and annotation bias | RF,NB,SVM, XGBOOST,L STM, CNN | Statistics,TF- IDF,BoW,Word2 vec | Reddit’s SuicideWatch BBS | Accuracy= 93.8% (LSTM-CNN  combined) |
| Learning |  | classificati |  |  |  |  |  |
| [29] |  | on |  |  |  |  |  |
|  |  | approach |  |  |  |  |  |
|  |  | es |  |  |  |  |  |
|  |  | To |  |  | GloVe embedding, MIMIC  embedding, GloVe Twitter embedding, | No specific dataset is given but they used dataset of suicide-related tweets collected from Twitter streaming data |  |
|  |  | investigat |  |  |  |
|  |  | e |  |  |  |
| Extracting |  | technique |  |  |  |
| psychiatric |  | s for |  |  |  |
| stressors |  | recognizi |  |  |  |
| for suicide  from social  media | Du et al (2018) | ng suicide  related  psychiatri | \_ | CNN, Bi-LSTM | Accuracy- CNN  (74%), Bi-LSTM  (72%) |
| using Deep |  | c stressors |  |  |  |
| Learning |  | from |  |  |  |
| [30] |  | Twitter |  |  |  |
|  |  | using |  |  |  |
|  |  | Deep |  |  |  |
|  |  | Learning |  |  |  |
| Early |  | To proposed a hybrid model that can detect depressio n by analyzing user’s textual posts. |  |  | Trainable Embedding, GloveEmbeddin g, Word2VecEmbe dding, FastextEmbeddi ng, Metadata |  |  |
| Depression |  |  |  |  |  |
| Detection |  | Used only |  |  |  |
| from Social  Network  Using Deep | Shah et al (2020) | one Deep  Learning  classifier in | Bi-LSTM | Reddit dataset | f1 score - 81%  (Word2VecEmbe  d+Meta) |
| Learning |  | this paper |  |  |  |
| Techniques |  |  |  |  |  |
| [31] |  |  |  |  |  |

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **PAPER TITLE [ID]** | **AUTHORS (YEAR)** | **OBJECTIVE** | **LIMITATIONS** | **TECHNIQUES** | **FEATURES** | **DATASET** | **REPORTED RESULT** |
| CEASE, a |  | To develop various Deep Learning models to perform emotion detection. | Divided the emotion in very vast category that’s why they got less accrucy |  |  |  |  |
| Corpus of |  |  |  | manual |  |
| Emotion |  |  |  | scavenging of | Accuracy- CNN |
| Annotated | Ghosh et | CNN, GRU, | GloveEmbeddin | actual | (59.54%), |
| Suicide | al (2020) | LSTM | g | suicide notes | GRU(58.70%), |
| notes in |  |  |  | from the | LSTM(58.08%) |
| English |  |  |  | internet. |  |
| [32] |  |  |  |  |  |
| An |  | To show |  | SVM,CNN,K NN,RF,Naiv e Bayes,LSTM |  |  |  |
| Investigati |  | the ability |  |  |  |  |
| on of Deep |  | to predict | Skip-gram |  |  |  |
| Learning | Morales | suicide | when facing | BoW,POS,Word | Reddit & | F1-score of .57 |
| Systems for | et al | attempts | out-of- | Embeddings,To | subreddit's | and .48 |
| Suicide | (2019) | has been | vocabulary | ne,syntax,NER | SuicideWatch | respectively. |
| Risk |  | near | words. |  |  |  |
| Assessmen |  | chance for |  |  |  |  |
| t [33] |  | decades. |  |  |  |  |
| Deep Learning Algorithm for Suicide Sentiment Prediction [34] | Boukil et al(2019) | To present an automate d detection and predictio n system depressio n through analyzing | \_ | Naive Bayes,CNN, KNN | BoW,TF-IDF | Suicide & Nonsuicidial notes,several Websites (Facebook, Twitter etc) | Accuracy=86.61%( Sentiment analysis and linguistic features with the logistic tree regressor algorithm) |
|  |  | sentiment s and feelings |  |  |  |  |  |

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **PAPER TITLE [ID]** | **AUTHORS (YEAR)** | **OBJECTIVE** | **LIMITATIONS** | **TECHNIQUES** | **FEATURES** | **DATASET** | **REPORTED RESULT** |
| Automatic identificati on of suicide notes with a transforme r-based deep learning model [35] | Zhang et al (2021) | classifyin g suicide notes collected from social media. | collect more precise data from different social media and  groups of people. Semi- supervised and unsupervise  d approaches are not used.  It is not directly interpretable so not suitable for clinical decision- making process | J48, Naive Bayes, Bayes Net, LMT, CNN, Bi- LSTM, Bi-  LSTMAttenti on, DLSTMAtten tion, Transformer RNN | linguistic and psychological features | Last Statements: Texas Department of Criminal Justices (2019) Suicide Notes: Kaggle's Suicide NotesSuicide notes  Neutral posts: ten subreddits | F1-score: 94.9%  (TransformerRN N) |
| Deep Learning for Suicide and Depression Identificati on with  Unsupervis ed Label Correction [36] | Haque et al (2021) | suicide versus depressio n classificati on method through a Deep Learning approach. | There is no way to evaluate which posts are accurate. | BERT  embeddings with a CNN (bert-cnn), BERT with a fully-dense neural network (bert-dense), BERT with a Bi-LSTM  neural network (bert-Bi- LSTM),  and GUSE with a fully- dense neural network (guse-dense).  UMAP  K-Means and GMM | (TFIDF, CVec,  HVec) | Reddit C-SSRS Dataset + Pang and Lee Movie Review Dataset | AUC: 98.18  (guse-dense with UMAP-KMeans) |

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| --- | --- | --- | --- | --- | --- | --- | --- |
| **PAPER TITLE [ID]** | **AUTHORS (YEAR)** | **OBJECTIVE** | **LIMITATIONS** | **TECHNIQUES** | **FEATURES** | **DATASET** | **REPORTED RESULT** |
| Using text mining to extract depressive symptoms and to validate the diagnosis of major depressive disorder from electronic health records [37] | C.-S. Wu,  et al. (2019) | evaluate the accuracy of diagnosti c codes and use text mining to extract symptom profile | Clinical and research implications | CNN, Bi- LSTM | Words,Part-of- speech tags,Symptom- and function- dictionary in the CRF model. | Integrated Medical Database,psych iatric diag- nosis (ICD-9- CM: 290–319 or ICD-10-CM: F00-F99) | F-scores of 0.774–  0.753. |
| Deep graph neural network‐ based prediction of acute suicidal ideation in young adults [38] | Choi et al (2021) | To develope d and validated a deep graph neural network model that increased the predictio n sensitivity of suicide risk in young using multi- dimensio nal questionn aires | Prediction of major depressive episodes using small datasets | SVM,CNN,L R,GNN | PHQ-9,PHQ\_5,  PHQ\_6, and PHQ\_8,SMOTE-  NC,PHQ\_2 and STAI-S,pseudo- labels for the MaDE section | CNG the presence of MDD,KAIST,G  achon University Hospital,Samsu ng Medical Center in Seoul,Seoul National University | Accuracy = 90.90%  (Combined SVM,GIN-MaDE  model) |

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| --- | --- | --- | --- | --- | --- | --- | --- |
| **PAPER TITLE [ID]** | **AUTHORS (YEAR)** | **OBJECTIVE** | **LIMITATIONS** | **TECHNIQUES** | **FEATURES** | **DATASET** | **REPORTED RESULT** |
| Deep neural networks detect suicide risk from textual facebook posts [39] | Ophir et al (2020) | To predict suicide risk from Facebook postings directly and a Multi- Task Model, which included hierarchic al. | Offine, external validations of suicide risk,mental health conditions in general and suicide risk in particular | ML,NLP,EL Mo,ANN | CWE  representation method, ANN modeling, psychodiagnosti c measures, and analysis of everyday language,TF- IDF | Facebook | [AUC=0.621, 95%  CI: 0.576,  0.657] |
| A Deep Learning model for detecting mental illness  from user content on social media [40] | Kim et al (2020) | Develope d a Deep Learning model to identify a user’s mental state based on his/her posting informati on. | Can't explain the difference between socio- demographic and regional.  In future study, adopting an ensemble approach with multiple binary classifcation  models, | Synthetic minority over- sampling,CN N | TF-  IDF,Continuous bag-of-words representation (CBoW) models | six mental- health-related subreddits, r/depression, r/Anxiety, r/bipolar, r/BPD, r/schizophrenia, r/autism and r/mentalhealth | F1-score of (96.96%) |
| An optimized Deep Learning approach for suicide detection through Arabic  tweets [41] | Baghdadi et al (2020) | To analysis of social media data allows for the discreet detection of depressiv e symptom s | \_ | CNN, RNN,LSTM,  and GRU | No Features used | Arabic tweets dataset,Twitter tweets,KAGGL E  datasets |  |

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| --- | --- | --- | --- | --- | --- | --- | --- |
| **PAPER TITLE [ID]** | **AUTHORS (YEAR)** | **OBJECTIVE** | **LIMITATIONS** | **TECHNIQUES** | **FEATURES** | **DATASET** | **REPORTED RESULT** |
| Detecting and Analyzing Suicidal Ideation on Social Media Using Deep Learning and Machine Learning  Models [42] | Aldhyani et al (2022) | Proposed a methodol ogy based on experime ntal research for building a suicidal ideation detection system using publicly available Reddit datasets,. | Handling words that are not in the selected vocabulary size as maximum features, it is nevertheless optimal for NLP tasks. | CNN,Bi- LSTM,SVM, NLTK,ML  XG Boost | textual,LIWC,TF  -IDF,Word Embedding | Reddit,50,000 tweets,Russian social networking platform | 91.5% accuracy using LIWC features, |
| A  Multitask Framework to Detect Depression  , Sentiment and Multi‐ label Emotion from Suicide Notes [43] | Ghosh et al(2021) | Focuses on learning three closely related tasks, viz. depressio n detection, sentiment citation, and to investigat e their impact in analysing the mental state of the victims. | Does not allow  to capture other secondary emotions for the sentences that  also carry vital emotional traits. | NLP,DL,ML | No Features used | 900 suicide notes,The  CEASE,Ekman’ s notion of emotion,4932 instances and annotated  for depression, sentiment and emotion labels. | 75.34 % accuracy |

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| --- | --- | --- | --- | --- | --- | --- | --- |
| **PAPER TITLE [ID]** | **AUTHORS (YEAR)** | **OBJECTIVE** | **LIMITATIONS** | **TECHNIQUES** | **FEATURES** | **DATASET** | **REPORTED RESULT** |
| A  Quantitativ e and Qualitative Analysis of Suicide Ideation Detection using Deep Learning [44] | Long et al (2022) | Evaluated the feasibility of detecting suicidal ideation using multiple datasets and different state-of- the-art Deep Learning models. | Not generalisable  ,No standard or perfect solution for selecting and preparing features | CNN,RNN,B I-LSTM | TF-IDF,300  features rotation forest | Twitter,consisti ng of 660 tweets,UMD Reddit Suicidality,BER T,RoBERT | Accuracy range of 45%-60% |
| VAD-  assisted multitask transforme r framework for emotion  recognition and intensity prediction on suicide notes [45] | Ghosh et al (2023) | The main objective of this paper to introduce s an end- to-end VAD-  assisted transform er-based multi-task network for detecting emotion and its intensity in suicide notes. | Small, imbalanced dataset and the lack of a measure that assesses the history of suicide attempts. | CNN,LSTM, SVM | word embeddings,VA D | suicide notes, CEASE- v2.0,VAD-BERT | F1 Scores 86.86% |

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **PAPER TITLE [ID]** | **AUTHORS (YEAR)** | **OBJECTIVE** | **LIMITATIONS** | **TECHNIQUES** | **FEATURES** | **DATASET** | **REPORTED RESULT** |
| Suicidal ideation and mental disorder detection with attentive relation networks [46] | Ji et al (2021) | Enhances text represent ation with lexiconba sed sentiment scores and latent topics and proposes using relation networks to detect suicidal ideation and mental disorders with related risk indicators  . | Fails in predicting lowrisk suicidal ideation, with a similar performance to other baselines | LSTM,Bi- LSTM,CNN,  Fast Cash,RCNN, SSA,RA | word embeddings,TF- IDF | Twitter,UMD reddit,Reddit SWMH | Accuracy = 0.64 (Reddit SWMH, With RN) |
| Suicidal text detection [47] | Yi et al (2022) | To build a predictive model to detect suicidal intent in social media posts | \_ | Logit,CNN,L STM,Bert,Ele ctra | Word 2 vec,glove | Suicide and depression detection dataset | Accuracy = 0.97 (electra) |

Table 2.4: Year wise count of selected research papers on Deep Learning

|  |  |
| --- | --- |
| **Year** | **No of papers** |
| 2023 | 1 |
| 2022 | 3 |
| 2021 | 5 |
| 2020 | 6 |
| 2019 | 3 |
| 2018 | 1 |
| Total = | 19 |

**Table 3.1: Examples and applications of Machine Learning:**

|  |  |  |  |
| --- | --- | --- | --- |
| **Category of ML** | **Technique** | **Example** | **Application** |
| Supervised | Classification | SVM | Text classification |
| Regression | SLR | Error Detection |
| Unsupervised | Clustering | K-MEANS | Image segmentation |
| Association | APRIORI | Grocery store |
| Semi-supervised | Merging clustering | - | Image analysis |
| Classification algorithms | - | Speech analysis |
| Reinforcement | Positive | - | Video games |
| Negative | - | Text mining |

Table 8.1: Coding environment and system details

|  |  |
| --- | --- |
| ***OS Name*** | Windows 10 Home Single Language |
| ***Version*** | 22H2(10.0.19045) |
| ***OS Manufacturer*** | Microsoft Corporation |
| ***System Type*** | x64-based PC |
| ***Processor*** | Intel(R) Core(TM) i3-8130U CPU @ 2.20GHz 2.20 GHz |
| ***BIOS Version/Date*** | F.43/16-11-2022 |
| ***Baseboard Manufacturer*** | Intel Corporation |
| ***Platform*** | GOOGLE COLAB |
| ***System Directory*** | C:\WINDOWS\system64 |
| ***Installed Physical Memory (RAM)*** | 4.00 GB |
| ***Total Physical Memory*** | 3.93 GB |
| ***Available Physical Memory*** | 618 MB |
| ***Total Virtual Memory*** | 12.00 GB |
| ***Available Virtual Memory*** | 4.56 GB |
| ***Page File Space*** | 5.56 GB |
| ***Device name*** | LAPTOP-S15FQ825 |

#### Reddit Dataset:

Table 9.1: Accuracy of Reddit Dataset using ML approach

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Features** | **ML Model** | | | | | | | | | | | |
| **SVM** | | | **NB** | | | **RF** | | | **LR** | | |
| 80:20 | 5-  Fold | 10-  Fold | 80:20 | 5-  Fold | 10-  Fold | 80:20 | 5-  Fold | 10-  Fold | 80:20 | 5-  Fold | 10-  Fold |
| BoW(1) | 69 | 78 | 76 | 73 | 82 | 82 | 77 | 78 | 78 | 69 | 78 | 78 |
| TF-IDF(1) | 73 | 80 | 80 | 77 | 78 | 78 | 77 | 78 | 78 | 77 | 79 | 79 |
| BoW(2) | 74 | 77 | 78 | 51 | 53 | 53 | 77 | 78 | 78 | 74 | 78 | 78 |
| TF-IDF(2) | 77 | 78 | 78 | 77 | 78 | 78 | 77 | 78 | 78 | 77 | 78 | 78 |
| TF-IDF(1) + BoW(1) | 69 | 77 | 77 | 73 | 82 | 81 | 77 | 78 | 78 | 69 | 79 | 78 |
| TF-IDF(1) + BoW(2) | 74 | 77 | 77 | 50 | 54 | 53 | 77 | 78 | 78 | 73 | 78 | 78 |
| TF-IDF(1) + TF-IDF(2) | 75 | 80 | 81 | 77 | 78 | 78 | 77 | 78 | 78 | 77 | 79 | 79 |
| TF-IDF(2) + BoW(1) | 69 | 77 | 77 | 75 | 81 | 81 | 77 | 78 | 78 | 69 | 78 | 78 |
| TF-IDF(2) + BoW(2) | 74 | 77 | 78 | 55 | 59 | 58 | 77 | 78 | 78 | 74 | 78 | 78 |
| BoW(1) + BoW(2) | 74 | 79 | 79 | 62 | 67 | 66 | 77 | 78 | 78 | 73 | 80 | 80 |
| TF-IDF(1) + TF-IDF(2)  + BoW(1) | 68 | 78 | 77 | 76 | 80 | 81 | 77 | 78 | 78 | 70 | 78 | 78 |
| TF-IDF(1) + TF-IDF(2)  + BoW(2) | 74 | 77 | 77 | 57 | 60 | 59 | 77 | 78 | 78 | 73 | 78 | 77 |
| TF-IDF(1) + BoW(1) + BoW(2) | 74 | 79 | 79 | 61 | 67 | 67 | 77 | 78 | 78 | 73 | 80 | 80 |
| TF-IDF(2) + BoW(1) + BoW(2) | 74 | 79 | 79 | 62 | 70 | 68 | 77 | 78 | 78 | 73 | 80 | 80 |
| TF-IDF(1) + TF-IDF(2)  + BoW(1) + BoW(2) | 74 | 80 | 79 | 66 | 70 | 68 | 77 | 78 | 78 | 73 | 81 | 80 |

#### SDCNL:

Table 9.2: Accuracy of SDCNL Suicide Dataset using ML approach

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Features** | **ML Model** | | | | | | | | | | | |
| **SVM** | | | **NB** | | | **RF** | | | **LR** | | |
| 80:20 | 5-  Fold | 10-  Fold | 80:20 | 5-  Fold | 10-  Fold | 80:20 | 5-  Fold | 10-  Fold | 80:20 | 5-  Fold | 10-  Fold |
| BoW(1) | 68 | 66 | 65 | 66 | 67 | 66 | 67 | 63 | 63 | 67 | 68 | 67 |
| TF-IDF(1) | 68 | 69 | 68 | 65 | 66 | 67 | 66 | 66 | 64 | 70 | 71 | 69 |
| BoW(2) | 56 | 56 | 56 | 59 | 59 | 59 | 59 | 52 | 54 | 59 | 59 | 59 |
| TF-IDF(2) | 60 | 59 | 58 | 63 | 60 | 60 | 58 | 52 | 54 | 60 | 56 | 56 |
| TF-IDF(1) + BoW(1) | 69 | 67 | 65 | 66 | 67 | 66 | 68 | 65 | 65 | 68 | 68 | 68 |
| TF-IDF(1) + BoW(2) | 62 | 61 | 61 | 60 | 60 | 60 | 63 | 62 | 62 | 62 | 62 | 62 |
| TF-IDF(1) + TF- IDF(2) | 70 | 70 | 68 | 69 | 68 | 67 | 65 | 62 | 62 | 71 | 70 | 69 |
| TF-IDF(2) + BoW(1) | 66 | 67 | 66 | 68 | 67 | 66 | 62 | 59 | 59 | 68 | 68 | 68 |
| TF-IDF(2) + BoW(2) | 56 | 56 | 56 | 62 | 59 | 59 | 56 | 54 | 54 | 60 | 59 | 59 |
| BoW(1) + BoW(2) | 67 | 66 | 64 | 65 | 65 | 64 | 66 | 59 | 58 | 71 | 69 | 68 |
| TF-IDF(1) + TF-  IDF(2) + BoW(1) | 66 | 67 | 66 | 68 | 66 | 66 | 68 | 63 | 61 | 68 | 68 | 68 |
| TF-IDF(1) + TF-  IDF(2) + BoW(2) | 63 | 61 | 60 | 61 | 60 | 60 | 62 | 61 | 61 | 62 | 62 | 62 |
| TF-IDF(1) + BoW(1) + BoW(2) | 69 | 66 | 66 | 66 | 65 | 65 | 66 | 62 | 62 | 71 | 69 | 68 |
| TF-IDF(2) + BoW(1) + BoW(2) | 67 | 66 | 65 | 65 | 64 | 64 | 65 | 58 | 59 | 70 | 68 | 68 |
| TF-IDF(1) + TF-  IDF(2) + BoW(1)  + BoW(2) | 69 | 66 | 66 | 66 | 65 | 65 | 67 | 63 | 62 | 71 | 69 | 68 |

#### SDD Dataset:

Table 9.3: Accuracy of SDD Dataset using ML approach

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Features** | **ML Model** | | | | | | | | | | | |
| **SVM** | | | **NB** | | | **RF** | | | **LR** | | |
| 80:20 | 5-  Fold | 10-  Fold | 80:20 | 5-  Fold | 10-  Fold | 80:20 | 5-  Fold | 10-  Fold | 80:20 | 5-  Fold | 10-  Fold |
| BoW(1) | 91 | 90 | 90 | 90 | 90 | 90 | 81 | 80 | 80 | 93 | 92 | 92 |
| TF-IDF(1) | 93 | 93 | 93 | 91 | 90 | 90 | 83 | 83 | 83 | 92 | 92 | 92 |
| BoW(2) | 90 | 90 | 90 | 91 | 90 | 90 | 79 | 78 | 79 | 91 | 90 | 90 |
| TF-IDF(2) | 92 | 91 | 91 | 89 | 89 | 90 | 80 | 80 | 80 | 89 | 90 | 90 |
| TF-IDF(1) + BoW(1) | 92 | 91 | 91 | 91 | 91 | 91 | 82 | 82 | 82 | 93 | 92 | 92 |
| TF-IDF(1) + BoW(2) | 92 | 91 | 91 | 91 | 91 | 91 | 80 | 81 | 80 | 92 | 91 | 92 |
| TF-IDF(1) + TF- IDF(2) | 94 | 93 | 93 | 92 | 91 | 91 | 81 | 81 | 81 | 93 | 93 | 93 |
| TF-IDF(2) + BoW(1) | 92 | 91 | 91 | 91 | 91 | 91 | 81 | 81 | 80 | 93 | 92 | 92 |
| TF-IDF(2) + BoW(2) | 91 | 90 | 90 | 91 | 91 | 91 | 80 | 79 | 79 | 91 | 90 | 90 |
| BoW(1) + BoW(2) | 92 | 92 | 92 | 91 | 91 | 91 | 78 | 79 | 79 | 93 | 93 | 93 |
| TF-IDF(1) + TF-  IDF(2) + BoW(1) | 93 | 92 | 92 | 92 | 92 | 92 | 82 | 81 | 81 | 93 | 92 | 92 |
| TF-IDF(1) + TF-  IDF(2) + BoW(2) | 92 | 91 | 91 | 92 | 91 | 91 | 80 | 80 | 80 | 92 | 91 | 92 |
| TF-IDF(1) + BoW(1) + BoW(2) | 92 | 92 | 92 | 92 | 91 | 91 | 80 | 80 | 80 | 93 | 93 | 93 |
| TF-IDF(2) + BoW(1) + BoW(2) | 92 | 92 | 92 | 91 | 91 | 91 | 81 | 80 | 80 | 93 | 93 | 93 |
| TF-IDF(1) + TF-  IDF(2) + BoW(1)  + BoW(2) | 93 | 92 | 92 | 92 | 92 | 92 | 80 | 80 | 80 | 93 | 93 | 93 |

#### Life\_Corpus:

Table 9.4: Accuracy of Life\_Corpus Suicide Dataset using ML approach

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Features** | **ML Model** | | | | | | | | | | | |
| **SVM** | | | **NB** | | | **RF** | | | **LR** | | |
| 80:20 | 5-  Fold | 10-  Fold | 80:20 | 5-  Fold | 10-  Fold | 80:20 | 5-  Fold | 10-  Fold | 80:20 | 5-  Fold | 10-  Fold |
| BoW(1) | 76 | 77 | 79 | 75 | 77 | 77 | 75 | 79 | 81 | 76 | 78 | 79 |
| TF-IDF(1) | 76 | 80 | 82 | 75 | 72 | 73 | 75 | 80 | 81 | 80 | 74 | 77 |
| BoW(2) | 71 | 75 | 75 | 36 | 40 | 42 | 67 | 67 | 67 | 71 | 80 | 80 |
| TF-IDF(2) | 67 | 67 | 67 | 65 | 64 | 63 | 67 | 67 | 67 | 67 | 67 | 67 |
| TF-IDF(1) + BoW(1) | 78 | 77 | 78 | 78 | 78 | 80 | 78 | 81 | 82 | 76 | 78 | 79 |
| TF-IDF(1) + BoW(2) | 73 | 75 | 76 | 38 | 43 | 43 | 76 | 79 | 81 | 73 | 81 | 81 |
| TF-IDF(1) + TF- IDF(2) | 78 | 80 | 82 | 76 | 73 | 73 | 73 | 78 | 81 | 76 | 72 | 76 |
| TF-IDF(2) + BoW(1) | 78 | 77 | 78 | 78 | 77 | 78 | 76 | 79 | 79 | 76 | 78 | 79 |
| TF-IDF(2) + BoW(2) | 71 | 75 | 76 | 40 | 50 | 51 | 67 | 67 | 67 | 71 | 81 | 80 |
| BoW(1) + BoW(2) | 80 | 81 | 80 | 60 | 65 | 66 | 80 | 77 | 81 | 78 | 81 | 81 |
| TF-IDF(1) + TF-  IDF(2) + BoW(1) | 78 | 77 | 79 | 78 | 78 | 80 | 75 | 78 | 82 | 76 | 78 | 79 |
| TF-IDF(1) + TF-  IDF(2) + BoW(2) | 73 | 75 | 76 | 47 | 52 | 54 | 80 | 75 | 78 | 73 | 81 | 81 |
| TF-IDF(1) + BoW(1) + BoW(2) | 80 | 80 | 80 | 67 | 69 | 68 | 76 | 80 | 81 | 78 | 81 | 82 |
| TF-IDF(2) + BoW(1) + BoW(2) | 80 | 80 | 80 | 69 | 76 | 74 | 76 | 78 | 80 | 78 | 81 | 82 |
| TF-IDF(1) + TF-  IDF(2) + BoW(1)  + BoW(2) | 80 | 80 | 80 | 71 | 76 | 76 | 78 | 81 | 81 | 78 | 81 | 82 |

#### CEASE:

Table 9.5: Accuracy of CEASE Suicide Dataset using ML approach

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Features** | **ML Model** | | | | | | | | | | | |
| **SVM** | | | **NB** | | | **RF** | | | **LR** | | |
| 80:20 | 5-  Fold | 10-  Fold | 80:20 | 5-  Fold | 10-  Fold | 80:20 | 5-  Fold | 10-  Fold | 80:20 | 5-  Fold | 10-  Fold |
| BoW(1) | 76 | 77 | 78 | 73 | 72 | 72 | 63 | 65 | 65 | 76 | 77 | 77 |
| TF-IDF(1) | 78 | 77 | 77 | 75 | 73 | 74 | 62 | 65 | 65 | 72 | 73 | 73 |
| BoW(2) | 70 | 73 | 72 | 63 | 63 | 63 | 62 | 65 | 65 | 71 | 71 | 71 |
| TF-IDF(2) | 72 | 72 | 72 | 67 | 68 | 68 | 62 | 65 | 65 | 65 | 67 | 67 |
| TF-IDF(1) + BoW(1) | 75 | 76 | 77 | 67 | 72 | 72 | 62 | 66 | 66 | 77 | 77 | 77 |
| TF-IDF(1) + BoW(2) | 73 | 75 | 75 | 68 | 67 | 66 | 62 | 65 | 65 | 72 | 73 | 74 |
| TF-IDF(1) + TF- IDF(2) | 79 | 77 | 78 | 73 | 72 | 72 | 67 | 65 | 65 | 77 | 74 | 74 |
| TF-IDF(2) + BoW(1) | 77 | 78 | 79 | 73 | 71 | 72 | 63 | 65 | 65 | 78 | 77 | 77 |
| TF-IDF(2) + BoW(2) | 69 | 72 | 72 | 62 | 61 | 62 | 62 | 65 | 65 | 71 | 71 | 71 |
| BoW(1) + BoW(2) | 76 | 77 | 78 | 70 | 68 | 69 | 62 | 65 | 65 | 76 | 77 | 77 |
| TF-IDF(1) + TF-  IDF(2) + BoW(1) | 78 | 78 | 78 | 72 | 71 | 72 | 63 | 65 | 65 | 77 | 77 | 77 |
| TF-IDF(1) + TF-  IDF(2) + BoW(2) | 73 | 75 | 75 | 67 | 65 | 65 | 62 | 65 | 65 | 73 | 74 | 74 |
| TF-IDF(1) + BoW(1) + BoW(2) | 77 | 78 | 78 | 71 | 69 | 70 | 63 | 65 | 65 | 77 | 77 | 78 |
| TF-IDF(2) + BoW(1) + BoW(2) | 76 | 77 | 78 | 69 | 67 | 68 | 62 | 65 | 65 | 77 | 77 | 77 |
| TF-IDF(1) + TF-  IDF(2) + BoW(1)  + BoW(2) | 76 | 78 | 78 | 70 | 68 | 69 | 63 | 65 | 65 | 77 | 77 | 78 |

#### SWMH:

Table 9.6: Accuracy of SWMH Suicide Dataset using ML approach

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Features** | **ML Model** | | | | | | | | | | | |
| **SVM** | | | **NB** | | | **RF** | | | **LR** | | |
| 80:20 | 5-  Fold | 10-  Fold | 80:20 | 5-  Fold | 10-  Fold | 80:20 | 5-  Fold | 10-  Fold | 80:20 | 5-  Fold | 10-  Fold |
| BoW(1) | 48 | 76 | 76 | 47 | 78 | 78 | 53 | 70 | 69 | 48 | 79 | 79 |
| TF-IDF(1) | 48 | 80 | 80 | 47 | 77 | 77 | 52 | 75 | 74 | 50 | 81 | 82 |
| BoW(2) | 52 | 74 | 74 | 47 | 77 | 77 | 53 | 56 | 56 | 51 | 77 | 77 |
| TF-IDF(2) | 51 | 77 | 78 | 52 | 78 | 78 | 53 | 62 | 62 | 53 | 79 | 79 |
| TF-IDF(1) + BoW(1) | 50 | 76 | 76 | 48 | 78 | 78 | 53 | 73 | 73 | 51 | 79 | 79 |
| TF-IDF(1) + BoW(2) | 52 | 75 | 75 | 47 | 77 | 78 | 53 | 62 | 62 | 51 | 79 | 79 |
| TF-IDF(1) + TF- IDF(2) | 49 | 79 | 80 | 48 | 79 | 79 | 53 | 70 | 70 | 50 | 82 | 82 |
| TF-IDF(2) + BoW(1) | 51 | 76 | 77 | 47 | 78 | 79 | 53 | 68 | 69 | 49 | 79 | 80 |
| TF-IDF(2) + BoW(2) | 50 | 74 | 75 | 47 | 77 | 78 | 53 | 59 | 59 | 50 | 77 | 78 |
| BoW(1) + BoW(2) | 50 | 77 | 77 | 47 | 78 | 78 | 53 | 62 | 62 | 51 | 80 | 80 |
| TF-IDF(1) + TF-  IDF(2) + BoW(1) | 49 | 77 | 77 | 48 | 78 | 78 | 53 | 72 | 72 | 48 | 79 | 80 |
| TF-IDF(1) + TF-  IDF(2) + BoW(2) | 52 | 75 | 76 | 47 | 78 | 78 | 53 | 64 | 63 | 51 | 79 | 79 |
| TF-IDF(1) + BoW(1) + BoW(2) | 54 | 77 | 77 | 47 | 78 | 78 | 53 | 66 | 66 | 54 | 80 | 80 |
| TF-IDF(2) + BoW(1) + BoW(2) | 51 | 77 | 77 | 47 | 78 | 78 | 53 | 64 | 63 | 51 | 80 | 80 |
| TF-IDF(1) + TF-  IDF(2) + BoW(1)  + BoW(2) | 51 | 77 | 77 | 47 | 79 | 79 | 53 | 66 | 66 | 51 | 80 | 80 |

Table 9.7: Accuracy of selected datasets using DL approach

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Dataset** | **Deep Learning** | | | | | | | | | |
| **LSTM** | | | **Bi-LSTM** | | | **CNN** | | | **BERT** |
| 80:20 | 5-Fold | 10-Fold | 80:20 | 5-Fold | 10-Fold | 80:20 | 5-Fold | 10-Fold | 80:20 |
| *Reddit Dataset* | 82 | 91.2 | 93 | 82 | 78.4 | 78.4 | 81 | 78.4 | 78.4 | 78 |
| *SDCNL* | 67 | 93.5 | 95 | 62 | 63.2 | 61.1 | 66 | 59.4 | 60.7 | 55 |
| *SDD Dataset* | 88 | 92.5 | 92 | 87 | 85 | 86 | 86 | 86 | 88 | 80 |
| *Life\_Corpus* | 85 | 90 | 92.8 | 85 | 68.2 | 70 | 87 | 67 | 57.4 | 85 |
| *CEASE* | 76 | 92.8 | 93.2 | 77 | 67.2 | 68 | 77 | 64.4 | 65 | 68 |
| *SWMH* | 71 | 87 | 91 | 73 | 73 | 74 | 68 | 70 | 71 | 60 |

#### Total Result Table:

Table 9.8: Best Accuracy of selected datasets using ML & DL approach

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Datasets** | **Machine Learning** | | | | **Deep Learning** | | | |
| **SVM** | **NB** | **RF** | **LR** | **BERT** | **LSTM** | **Bi-LSTM** | **CNN** |
| *Reddit Dataset* | 81 | 82 | 78 | 81 | 78 | **93** | 82 | 81 |
| *SDCNL* | 70 | 69 | 68 | 71 | 55 | **95** | 63 | 66 |
| *SDD Dataset* | **94** | 92 | 83 | 93 | 80 | 92 | 87 | 88 |
| *Life\_Corpus* | 81 | 80 | 81 | 81 | 85 | **93** | 85 | 87 |
| *CEASE* | 79 | 75 | 67 | 78 | 68 | **93** | 77 | 77 |
| *SWMH* | 80 | 79 | 75 | 82 | 60 | **91** | 74 | 71 |

#### Result of Proposed System 2:

Table 9.9: Accuracy of selected datasets using Proposed System 2

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Model** | **Datasets** | | | | | |
| **Reddit Dataset** | **SDCNL** | **SDD Dataset** | **Life\_Corpus** | **CEASE** | **SWMH** |
| *Proposed System 2* | 97.4 | 94.4 | 93.7 | 97.14 | 99.2 | 91.5 |

#### Comparison Table:

Table 9.10: Comparison of accuracy between existing research work and proposed work

|  |  |  |  |
| --- | --- | --- | --- |
| **Datasets** | **Authors** | **Technique / Features** | **Reported Result** |
| *Reddit Dataset* | Gupta et al. [11] | NB, Semantic Features | 71 |
| Proposed System 1 | LSTM | 82 |
| Proposed System 2 | Hybrid model | 97.4 |
| *SDCNL* | Proposed System 1 | LR, TF-IDF(1), TF-IDF(2) | 71 |
| Proposed System 2 | Hybrid model | 94.4 |
| Haque et al [36] | guse-dense with UMAP-KMeans | **98.18** |
| *SDD Dataset* | Proposed System 2 | Hybrid model | 93.7 |
| Proposed System 1 | SVM, TF-IDF(1), TF-IDF(2) | 94 |
| Yi et al [47] | Electra | **97** |
| *Life\_Corpus* | Caicedo et al [8] | Rasa | 0.49 ± 0.02 (Macro f1) |
| Parraga-Alava et al [20] | Hierarchical clustering. average | 0.79 (F1) |
| Proposed System 1 | CNN | 87 |
| Caicedo et al [16] | POS, SYNSETS, lemma, word RandomCommitte | 0.958 (F1) |
| Proposed System 2 | Hybrid model | **97.14** |
| *CEASE* | Ghosh et al [32] | CNN | 59.54 |
| Proposed System 1 | CNN | 77 |
| Proposed System 2 | Hybrid model | **99.2** |
| *SWMH* | Ji et al [46] | RN | 64 |
| Proposed System 1 | Bi-LSTM | 73 |
| Proposed System 2 | Hybrid model | **91.5** |