# Emotion Detection from Text and Analysis of Future Work: A Survey

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**Abstract**—Emotion detection has recently become a fascinating subject for academics, as people express their emotions in various ways, including through manners, words, writing, or facial expressions. With the increased use of social media and technological advancements, it has become easier to retrieve enormous emotions regularly. Unsurprisingly, social networks have become a suitable communication medium for users to interact with friends and share their emotions. Detecting emotion is a valuable and powerful tool for identifying and recognizing moods, with numerous uses that can impact diverse areas. Machine learning algorithms and approaches are used to find high-quality solutions for detecting emotional issues among social media users and different datasets. This survey focused on emotion detection and classified the most current state-of-the-art systems for textual emotion recognition based on methodology, emotional model, and several datasets. Our Conclusion aims to emphasize the limitations and gaps in these recent efforts, analyze the approach and detection technique, and suggest future research directions to fill these gaps in this rapidly evolving field. We highlighted different approaches to detecting emotion, including the current trending successful approach, and conducted a comparative study to reveal the algorithm's performance using other models, approaches, and methodologies.

**Keywords**—*Emotion detection, Machine learning, Text, Lexical, Supervised and Unsupervised learning, Hybrid approach*

## 1. Introduction

In today's fast-paced modern earth, mental health disorders like anxiety disorders, depression, schizophrenia, addictive demeanors, and stress significantly affect numerous people. Depression, in particular, is a prevailing illness worldwide, with millions of people of all ages experiencing its consequence. Often, someone experiencing these circumstances may find themselves withdrawing socially and feeling secluded. As social media platforms have increased in popularity, people have discovered comfort in attaching to others and expressing their thoughts, emotions, opinions, photos, videos, sentiments, and experiences—including their pain. Individuals with depression often use social media to connect with like-minded someones, communicate their emotional expeditions, and want Support from others in comparable circumstances. By analyzing human behavior, we can understand mental health's elaborateness and distinguish between normal and abnormal. Psychologists have long been capable of predicting human behavior through observation, investigation, and understanding. Besides, scholars in different fields utilize their determinations to predict outcomes based on the information. One such area of research interest is the analysis of emotion detection from social media data using Machine Learning techniques concerning contemporary trends, subjects, and conversations across the web, and researchers desire to determine the influence of textual information on individuals' mental circumstances by identifying their emotions [1]. Innumerous

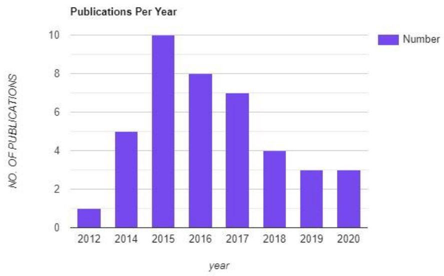


**Fig. 1.According per year, the number of publications used in this survey**

approaches have been analyzed to detect emotions from public text, using Machine Learning algorithms and classifiers such as Decision Trees, Support Vector Machines, Naive Bayes, Logistic Regression, and the K-Nearest Neighbor algorithm[2].
The extended volume of data generated by platforms like Twitter further highlights the effectiveness of this research, with millions of tweets being posted every second, denoting a priceless resource for emotion analysis [3] [43] [44] [45][46]. Likewise, the Study of Speech Emotion Recognition (SER) has garnered substantial interest in affective computing and human-computer interaction. From speech data, SER procedures aim to classify and recognize six basic emotions: anger, sadness, disgust, fear, happiness, and neutrality. Scholars in separate areas have concentrated on interpreting emotions from speech expressed in local languages to improve communication between people and technology [4]. Moreover, mental solidity and stress management are essential concerns, especially in the tech industry. Researchers have employed Machine Learning algorithms to detect stress levels among tech professionals. Surveys and questionnaires have been conducted to collect data and evaluate stress in the workplace [5]. Additionally, advancements have been created in emotion recognition founded on physiological signals, as different passwords are utilized to detect human emotions. Scholars have investigated physiological signals generated by basic emotions and used different algorithms to perform emotion recognition based on these signals [6] [47][48]. Notably, text information can only capture a fraction of the emotional spectrum experienced by individuals, as emotions are complicated and multidimensional [7] [49][50]. Two types of expression of emotions are as follows:
1. Affective items: Words determine by the context which doesn't have direct assigning.
2. Emotive items: Assigning to emotional category (happy, sad, love, etc).
This survey aims to analyze the model and techniques used by different researchers. We also discuss the approaches, datasets, and evaluation techniques. The number of publications per year is shown in Fig 1. The overall survey shows a comparative analysis and classifies the recent and most significant emotion detection work. This paper is assembled as follows: Related Studies and Methodology are discussed in sections II and III. The evaluation process is presented in section IV. The comparative Study is shown in section V. Discussion, and Conclusion are listed in sections VI and VII.


**Fig. 2.Word cloud on this paper**

## 2. Related Work

S.A.Salam et al. [1] represented a system that can detect eight basic emotions. The dataset originated from the tweeter, and supervised, and unsupervised machine learning methods were performed. The authors pointed to NB, SVM, and KNN algorithms for comparison, where the SVC with (5 fold cross-validation) approach shows the best conduct for this proposed system.

Souza et al. [2] worked on a hybrid process based on both research and machine learning which is required in this document to separate the six categories of Ekman (enjoyment, fear, anger, surprise, sadness, and disgust) emotions in the user text. They use many techniques to test how it performs in emotional awareness to validate a suggested strategy. Due to inaccessible conditions, the hybrid method has significantly improved all performance metrics and substantially reduced poorly classified requirements. Based on two different domains and scenarios to demonstrate the benefits of a hybrid approach to emotional recognition.

Manamela et al. [4] discussed the Speech Emotion Recognition (SER) program and recognized six fundamental feelings (sadness, disgust, anger, fear, neutrality, and joy) in the Sepedi language. Recorded speeches were gathered from Sepedi language speakers and a television drama radio to create an emotional compilation. Thirty-four speaking features were extracted from the talking corpora, using the audio analysis tool, training, and comparing various algorithms by using 10 folds of checks the assessments performed using the WEKA data mining software program. The outcomes showed that auto-WEKA surpasses all widespread algorithms (SVM, KNN, and MLP).

Jang et al. [6] classified three emotions (pain, boredom, and surprise) using multi-channel physiological signals to identify the optimal algorithms to detect them. We used Decision Tree, KNN, LDA, and SVM for emotion classification.

Reddy et al.[8] implemented a system that can automatically categorize and identify text. Here data is collected by conversation from counseling. All these data are processed through a machine learning algorithm. Processed data are visualized and classified into different categories. It helps psychology professionals to understand the problem of the patient. Especially Interns can give therapy according to the patient's concern which is categorized.SVM, Word vectorization used to analyze and classify the problem.

Sana et al. [9] created a business criterion using Urdu. But other language systems and this language system do not match the process of business systems. The additional signals from another expression supported this paper. It also represents a business-related emotion recognition system in Urdu for classification on social media websites in the business domain. They calculated the result using machine learning algorithms to detect emotion in business-related reviews.

Junianto et al. [10] made a good vision in this research. The Internet has a significant impact on human life. Through social media, people are connected with everyone. One person can talk about others on these platforms. Various comments poke on the Internet influence real life too. This article researcher describes a system that can filter positive and negative comments or text from social media text comments. Swarm optimizer and Naive Bayes machine learning algorithm are mainly used in implementation here to find positive and negative comments.

Grover et al. [11] implemented their system by Punjabi text in Unicode Transformation format using Python. The targeted categories of emotions were six senses(happy, sad, angry, scared, disgusted, and surprised). The emotion recognition process includes preprocessing steps, feature detection, and detection of emotions and isolation. The tested results show that the proposed design works well enough to capture the emotions in the Punjabi text.

Guo et al. [12] suggest an integrated body approach to acquiring the emotional response of the system involved. The physiological procedure uses EEG signals and participants' facial expressions and state-of-the-art signal processing techniques, including CS, LBP, and wavelet, to take out distinguishing features. The positive structure of the emotional response phase issue the new FCM-SVM segment with features of EEG and facial attributes face of the'' NNP'' aircraft. The system controls familiarity with emotional categories by incorporating the emotional model's description, the feature's output, and the algorithm learning design.

Azmin et al. [13] studied human emotion detection from the Bangla text format. Existing research has been done in different languages. Nowadays, people can share their feelings in the virtual world. So, it becomes a platform for research activity. All data that are used in this project are collected from Facebook. Artificial Intelligence and Natural Language Processing (NLP) are being used. The naive Bayes Classifier was implemented to detect three emotions, and these are sad, happy, and angry. It is the first work in the Bangla language context.

Healy et al. [14] bring an innovative city concept. Psychology is a primary human thing. Society has a variety of different psychological matters. School students may have mental disturbances which will affect the family. There is an interdependence system. In this paper, the researcher discussed an overall psychology monitoring system. Where different psychological crises are measured on various scales and levels. ISOMAP algorithm, K-means cluster is followed to classify the psychological states with machine learning techniques.

## 3. Methodology

For forecasting detection emotion, machine learning algorithms are beneficial. These applications help society by acting as real-time surveillance tools for people with diverse habits. The numerous techniques and approaches for detecting emotion from the text are briefly discussed in this part, and further specifics concerning text processing and datasets are essential elements.

*A. Approaches of emotion detection from text*

Four types of approaches are found that can detect emotions from the text. They are as follows:

1. Keyword-Based Approach

This is a na¨ıve approach and the easiest effective way to detect emotions in writing or a speech from a sentence. According to this approach, a text report carrying one or more than one sentences is considered input. After that, they are divided into tokens, and emotional words are separated and taken out from all tokens; after that, the frequency of emotional words is gathered by counting the words. In the end, the output will be given for this input which contains the emotional class. Occasionally, lexical words help classify emotions, which will be the take of inventory words representing the best emotions. Even so, this approach fails when the emotions are correlated with words.

2. Lexical /Corpus-Based Approach The lexical/corpus-based approach, an expanded keyword-based approach, determines the probability or weight of an uninterrupted word for a specific emotion. It can be separated into two types lexicon-based with weights. Ontology-based emotions fundamental emotions are at the top of the emotion ontology with high weights, while branchlet emotions are at the bottom with low weights. The number of publications that used this method and their evaluation metric, also the dataset analyzed, are shown in Table 1. We also visualized the year-wise publication based on this approach, as shown in Fig. 3.

3. Learning-Based Approach

There are some constraints in lexical and keyword-based approaches to get over that this approach pursues data on its own and also seeks a relationship between the specified text and related outturn of emotion by constructing a predictive model rather than the requisite direct link on emotion from the inserted text. It can be ordered into two types: The number of research articles that used this approach and their evaluation metric; the dataset analyzed is shown in Table 2. We also visualized the year-wise publication based on this approach, as shown in Fig 4.

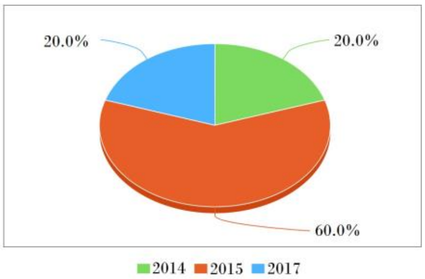


**Fig. 3.Per year of the paper derived from the Lexical approach**

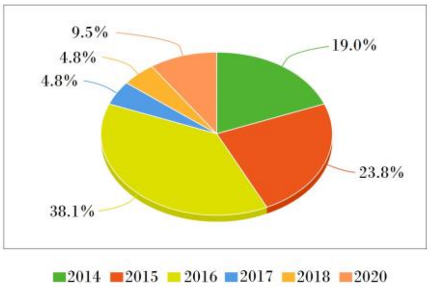


**Fig. 4.Per year of the paper derived from the learning approach**

A) Supervised approaches: This is formed on the tagged dataset. These data proceed for training to apply the emotion classifier. The data is trained, then explored, and the model is constructed. The rest of the dataset is classified into the emotion classifier categories based on trained data.

B) Unsupervised approaches: It is formed on non-tagged datasets. This approach assumes defects of the machine learning algorithm where a big-size dataset is needed for accurate training processing.

**4. Hybrid-Based Approach**

A few approaches can not provide satisfactory outcomes. The hybrid approach uses the previous combined approach for better-performed emotion detection. The number of research articles that used this approach and their evaluation metric also the dataset analyzed are shown in Table 3. We also visualized the year-wise publication based on this approach, as shown in Fig 5.

*B. Text Preprocessing*

Data preprocessing is the essential step in text classification [15]. Its main characteristics are it removes noisy data and unnecessary informative text from the main text, such as emojis, hashtags, etc. As a result, it helps improve the identification classification process performance. Many researchers applied the text preprocessing and general text preprocessing steps discussed below.

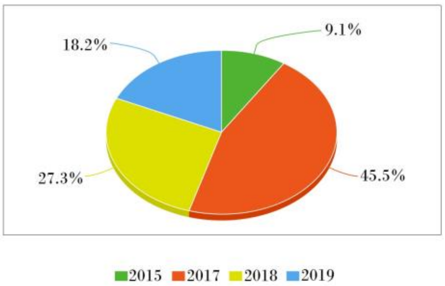


**Fig. 5.Per year of the paper derived from the Hybrid approach**

Noise removal: This step plays an important role. Its primary role is to remove unnecessary information (punctuation marks, numbers, non-Arabic text, special characters, etc.), which affects classifier performance.

Tokenization: this phase is significant; here, the text gets separated into a different tokens based on white space, tab, comma, etc.

Stemming: Stemming reduces the wording to its stems and removes the word's suffix according to specific grammatical rules.

Stop-word removal: These words with less information are commonly used, such as conjunctions and extensions.

The text preprocessing step of each paper is shown in Table 4.

*C. Dataset*

As we know, the dataset is a vital part of any experiment. It provides a lot of information. We can say it plays an essential role in any investigation or analysis. There are different and standard datasets that are used for the experiment. In this section, some of these datasets are discussed.

i)ISEAR: ISEAR (International Survey on Emotion Antecedents and Reactions): in the 1990s, all psychologists worldwide collected personal data based on human emotion on the ISEAR project, which Klaus R. Scherer and Harald Wallbott directed. It contains 7,666 sentences defined by participants from different cultures. They were asked to report experiences related to seven emotions: joy, fear, anger, sadness, disgust, shame, and guilt.

ii)Fairy Tales: it was developed by Cecilia Ovesdotter Alm, Richard Sproat, and others. It contains 15,000 sentences from 185 children's stories written by Beatrix Potter, Brother Grimm, and Hans Christian Andersen. They try to give manual labels by hand using one of the following emotions: anger, disgust, fear, happiness, sadness, positive surprise, negative surprise, or neutrality.

iii)SemEval 2007: SemEval 2007 workshop on shared affective computing work. It Contains news articles published in popular newspapers such as the New York Times, CNN, and BBC News, in addition to the Google News search engine.

iv)Social Media: Facebook, Twitter, Blogs, and YoTube is also the source of datasets.

v)News: Data is also collected from the different news channels.

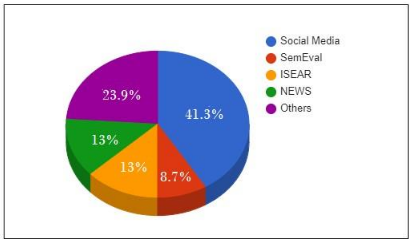


**Fig. 6.Dataset Sources**

A maximum number of scholars used multiple sources for the dataset. We focused here on visualizing the most used sources according to this survey. Fig 6 shows the sources of the dataset used by the scholars.

## 6. The Evaluation Process

The evaluating process of detecting emotion is convoluted and regarded as the composite process for many objects, the emotion is subjective here, and it varies by people, which may occur unbalanced dataset and the actual authentication of data in the dataset if it is how returns the real emotion as the assessed assertion.

The Inter-Annotator Agreement: Also referred to as inter-judge agreement, It's a metric for determining the best way to merge two or more annotators or judges of humans to arrive at equivalent annotation results. This thing is derived using the kappa coefficient; theoretically, it has a value of 0 to 1. A score of 0 indicates that the judge disagreed, whereas a score of 1 implies that all human assessments concur.

Precision and Recall: Precision is the capacity of the classifier to recognize positive emotions, whereas Recall refers is the proportion of the emotion observed.

F-Score: The F1 score, F value, or F measure. In a nutshell, the typical Precision and Recall are weighted equally. When the F score is more excellent, the performance is top-class. Approximative evaluation criteria include the F score, Accuracy, and memory.

Accuracy: The Accuracy of a machine learning model is used to determine its efficacy. In emotion detection investigations, precision signifies repeatability, whereas Accuracy denotes authenticity.

10-Fold Cross-Validation: The data is divided into ten sections. One is for testing, while the other is for training. An average score will be used to evaluate the entire performance after the test. Pearson

Correlation Coefficient: It's calculated the link between genuine and expected emotion probability. The coefficient is a granular metric for appraising a product.

**Table I.Summary Of The Paper Based On The Lexical Approach**

| Reference No. | Year | Language | Detection Technique | Evaluation metric | Dataset |
|---|---|---|---|---|---|
| [16] | 2014 | English | NRC has-tag Lexicon based | A Pearson's chi-square test | myPersonality(project) |
| [17] | 2015 | English | Based on the keyword approach | Judged by human | 135's Blog |
| [18] | 2015 | English | Lexicon based | 10-fold cross, Precision, Recall, and F-score | ISEAR ,SemEval and Twitter |
| [19] | 2015 | English | Lexicon-based: J48 DT | - | - |
| [20] | 2017 | English | Build an emotion lexicon | F-score | Twitter, news, and blogs |

**Table II.Summary Of The Paper Based On The Learning Approach**

| Reference No. | Year | Language | Detection Technique | Evaluation metric | Dataset |
|---|---|---|---|---|---|
| [8] | 2020 | English | SVM, Machine Learning | | |
| [9] | 2018 | Urdu | SVC, RF, NB, KNN | Accuracy, Precision, Recall, F1 measure, Support | Tweeter |
| [10] | 2020 | English | Machine Learning | Precision, Recall, Accuracy | WASAA |
| [21] | 2014 | Arabic | SVM, NB | F-measure, Precision, Recall | Tweeter |
| [22] | 2014 | English | Supervised, Machine Learning | Kappa Coefficient | Tweeter message |
| [23] | 2014 | English | Classifier | F1 score, Recall, Precision | Tweeter message |
| [24] | 2014 | Chinese | Machine Learning | Pearson correlation coefficient average | Site of ictclas.org news |
| [25] | 2015 | English | SVM, NB multilayer label classifier | F1 score, Precision, Accuracy | Tweeter |
| [26] | 2015 | English Chinese | Machine Learning | F1 score | Site weibo.com |
| [27] | 2015 | English | Naive Bayes (Supervised Learning) | 10 Fold cross-validation | 105 Tweets |
| [28] | 2015 | English | Machine Learning | Precision, Recall, Human Judgment, F1 score, Accuracy | 3600 samples |
| [29] | 2015 | Chinese | Logistic Regression | 10 Fold cross Validation, Recall, Precision | Sina News, Tencent news |
| [30] | 2016 | English | TME model | Accuracy, Avg precision, Pearson correlation avg | BBC, Myspace, Tweeter, Digg, World, |

| | | | | | |
|---|---|---|---|---|---|
| | | | | | Youtube, Runner |
| [31] | 2016 | Arabic | SVB, MNB | Precision, F score, Recall | Tweeter |
| [32] | 2016 | English | Unsupervised Machine Learning | Recall, Precision, Accuracy | Youtube comments |
| [33] | 2016 | English | Convolutional Neural Network | Accuracy | MOUD |
| [34] | 2016 | Portuguese | SVM, NB, RF, Cart DT | 10 Fold cross Validation Accuracy | Newspaper headlines |
| [35] | 2016 | English | Maximum entropy model, L- BFGS algorithm | F1 score, Accuracy | Semeval, SSTweet, ISEAR |
| [36] | 2016 | English | SVM | Precision, Recall, F1 score, Accuracy | Affective Text, Fairy Tales, ISEAR, Facebook |
| [37] | 2016 | Chinese | KNN, SVM | Squared X2, Intersection, KL divergence, and Fidelity, Euclidean | RenCECps corpus |
| [38] | 2017 | English | Dominant Meaning Classifier and Appraisal Method | Kappa coefficient. Average precision, Recall, F1 score | ISEAR |

## 7. Comparative Study

A comparative study shows a summary of the algorithm, evaluation metrics, and performance of the papers used by the scholars. The approach is a vital thing of research. We can easily differentiate the algorithm's performance and approaches from the comparative analysis. In this section, we analyze the approaches, detection techniques, evaluation metrics, publication year, algorithm performance, and dataset used in that paper that works to detect emotion. A comparative study is shown in Tables I, II, and III based on the approach, and Table IV shows the algorithm used to complete each research. The performance of the algorithm is also discussed.

## 8. Discussion

In the field of machine learning, there are numerous approaches. We have mentioned hybrid, linguistic, and learning-based approaches in this bar chart, and Figure 7 is shown that,

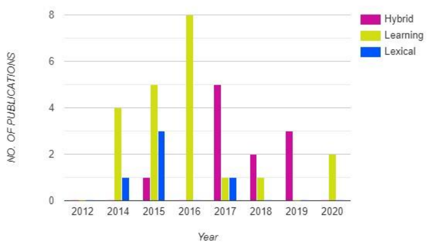


**Fig. 7. Number of publications derived from the Learning, Lexical, and Hybrid approach per year**

number of publications based on these approaches from 2012 to 2020. As illustrated, there are no publications in the year 2012. Only lexical and learning approaches were published in 2014; no hybrid approach was published in the same year. Respectively, 2014,2015,2016, and 2020 was the highest publication of the Learning-based approach. Most of the hybrid approaches were in 2017, 2018, and 2019. From Figure 3, We can see that in 2014, 20%. On the other hand, in 2015, it moved to 60%. But in the next year, in 2016 decreased to 20%. From the pie chart, it is clear that the learning approach is losing its popularity. In Conclusion, we can say that in 2015 it gained immense popularity, but after 2015, it lost its popularity because researchers found alternative approaches.

**Table III.Summary Of The Paper Based On The Hybrid Approach**

| Reference No. | Year | Language | Detection Technique | Evaluation metric | Dataset |
|---|---|---|---|---|---|
| [1] | 2018 | English | Hybrid (Lexicon Based, Supervised, Unsupervised Machine Learning) | 5- Fold cross-validation 10- Fold cross-validation Precision, Recall, F1 Score | Twitter |
| [2] | 2018 | English | Hybrid (Lexical Based SVM classifier) | Recall, Accuracy, F1- measure | ISEAR, SemEval |
| [3] | 2017 | English | Hybrid (Lexicon Based, Unsupervised Machine Learning | | Twitter |
| [4] | 2018 | Multiple Language | Hybrid (Lexicon and different classifier KNN, SVM, MLP Auto WEKA) | Precision, Recall, Accuracy, F-Measure | TV drama broadcast |
| [11] | 2017 | Panjabi | Hybrid (Keyword Based SVM, NB ) | | EEG Signal |
| [12] | 2019 | EEG Signal | Hybrid (SVM FCM Classifier) | | HC Corpora |
| [13] | 2019 | Bangla | Hybrid | F1-Score | Facebook |
| [39] | 2015 | English | Hybrid (Keyword Machine learning-based) | | YouTube video (Comment) |
| [40] | 2017 | Multiple Language | Hybrid (Lexicon based, NB SVM) | Precision, Recall, Accuracy, F-Measure | Sports Health Care Election |
| [41] | 2017 | Different Languages | Hybrid ( Machine Learning Lexicon Based ), With different classifiers (probabilistic Tree-Based, Statistical based | Precision, Recall, F1- Measure | Social media (Twitter, Facebook), NEWS Agencies |
| [42] | 2017 | English | An Ensemble Approach combining linear model-based and non-linear model-based | Avg F- score | Twitter, Post of Blogs, ISEAR, SemEval |

**TABLE IV.THE ALGORITHM USED AND THE PERFORMANCE**

| Reference No. | Algorithm | Performance |
|---|---|---|
| [1] | K-means, NB and SVM | The SVC approach (with 5-Fold validation) performs well. NBC and SVM are good from K-Means. |
| [2] | NLP, SVM | SVM-68.3% |
| [4] | KNN, SVM, MLP and Auto-WEKA | WEKA 100% and KNN 57.0% |
| [6] | DT, KNN, LDA,and SVM | LDA - 74.9% |
| [8] | SVM | SVM-63.5% |
| [9] | SVM,RF,NB ,KNN | Dataset1- SVC(80.50%),RF(76.00%),NB(76.00%),KNN(72.00%) |

| | | |
|---|---|---|
| | | Dataset2-SVC(81.09%),RF(67.66%), NB(58.71%),KNN(72.64%) |
| [10] | NBC, Particle Swarm Optimization(PSO) | NBC(65.93%),PSO+NBC(66.54% |
| [11] | SVM, NB | |
| [12] | SVM, FCM-SVM | Overall 75.64% Highest 81.2% |
| [13] | SVM, MNB | MNB(0.786), SVM(0.716) |
| [17] | Self-created algorithm | Average Precision-88.08%,Accuracy-79.57% |
| [18] | Non-Linear SVM | Average F-score:Anger-0.69,Fear-0.78,Joy-0.76,Sad-0.72 |
| [19] | LDF, KNN, MLP, J48 DT | J48:Anger-94%,Pleasurer-86%,Sadness-87%,Joy-98% |
| [22] | SVM, KNN | KNN above 90% |
| [23] | SVM, KNN, DT, and NB | KNN, SVM above 90% |
| [24] | FEM, ETM, ET, SWAT | FEM + POS + DS 60% |
| [29] | ET,NB,LDM,eLDM,SVM,LR,ETM | |
| [30] | SVM, NB | SVM:0.748 NB:0.757 |
| [32] | SVM | Average Accuracy; 68.82%, Precision:92.75% |
| [33] | RNN, CNN, MKL | Angry:79.20%,Sad:75.63%Happy:72.22%,Neutral:80.35% |
| [34] | SVM, NB, DT, RF | Accuracy: 55.91% |
| [35] | Maximum entropy model L-BFGS | Semeval: gMME 0.3696, MME 0.3249 SSTweet: gMME 0.9030, MME 0.8644 ISEAR: gMME 0.5486, MME 0.5023 |
| [36] | SVM | ISE-M 0.460(AVG micro f score) |

The evidence from Figure 4 shows how many papers have been published based on the Learning Approach from 2014 to 2020 and what percentage of the papers we have read. We can see 19% in 2014, 23.8% in 2015, and 38.1% in 2016. But in 2017 and 2018, only 1% of the papers were published. On the other in 2020, 9.5% of the papers were published. From the pie chart, it is clear that the learning approach is losing its popularity. In Conclusion, we can say that in 2016 it gained average popularity, but after 2016 every year, it lost its popularity, and researchers are attracted to other approaches. As depicted in Figure 5, we can observe that the majority hybrid approach was used in 2017. The second highest use was in the year of 2019, and relatively low usage in the year of 2018 and 2015. Most notably, it was used significantly less in 2015, and its use has vastly increased significantly in the following years.

**TABLE V.TEXT PREPROCESSING OF EACH PAPER**

| Reference No. | Language | Preprocessing |
|---|---|---|
| [1] | English | Replacing HTTP links using URLs, removing newlines, tabs, and hash characters, and transforming the data are all part of the data preprocessing approach. |
| [2] | English | Use text preprocessing techniques, including Tokenization, root word extraction, and stop word removal, before erasure the most informative characteristics from the annotated training dataset |
| [3] | English | Characters like HTTP, @, , www, URL,.,"," and other unwelcome characters can be found in tweets. |

| | | |
|---|---|---|
| | | To acquire meaningful material, all unnecessary content is cleaned and removed utilizing text mining tools. |
| [4] | Sepedi (South Africa) | There was a lot of background music (noise) on the television show, and some of the recordings were uneven and fragmented. Because the obtained data was not sufficiently cleaned, the noise had an impact on algorithm performance. |
| [10] | English | Transforming to Lower Cases, Tokenization, Filter Token (by Length), Stop Words, Stemming, Vector Creation |
| [11] | Punjabi | Segmentation, Tokenization, Stop word Removal, Stemming, also manually |
| [13] | Bangla | Text Segmentation, Handling Emoticons, Stop Word Removal, Stemming |
| [15] | English | removing contain URLs, hashtags, mentions, Emoticon, stemming, stopwords |
| [17] | English | Cleaning and Conversion |
| [21] | Arabic | Removing non-Arabic letters, punctuations, multiple spaces, stop words, and stemming |
| [22] | English | To drive the classifier algorithm, the hashtags were eliminated. |
| [23] | English | Tweets with unwelcome characters such as @, URL, and so on. Any tweet with different classes' hashtags is eliminated from the training set. Some tweets, for example, include emoticons from two separate categories. Conflicts between hashtags, emoticons, and repeated letters can be found in some tweets. All unnecessary information has been cleaned up and eliminated |
| [24] | Chinese | Segmentation |
| [25] | English | Stemming, stop word cleaning, and Tokenization |
| [27] | English | Change the uppercase to lowercase. Carry away the URL, mention it, erase a non-a-z letter, remove the stop-word, convert symbols to text, and combine denial with the word following refusal. |
| [31] | Chinese | Removing stop words, words emerging in less than 30 documents are rejected to reduce feature dimensions. |
| [32] | English | Stemming |
| [34] | Portuguese | Tokenization, Stop words Removal, Stemming |
| [38] | English | Removing stop words |
| [41] | English, Greek | Cleaning noises, Tokenization, stemming |
| [42] | English | Lemmatization |

*A. Future Work*

eep learning-based research in the future is encouraging, mainly if a wide-ranging and well-annotated dataset is available. Furthermore, future studies into constructing and identifying a correctly labeled global dataset will aid and accelerate progress in textual emotion recognition by providing a standard dataset against which to compare other planned research. In addition, Artificial Intelligence algorithms are incredibly beneficial for detecting emotion. In the future, we will originate a model that will detect the most likely impending emotion for each other user based on text. The system will be able to detect emotion based on the textual conversation of a user. If the emotional state is changed, the system will notify the user. We believe it would be helpful to forecast consumers' emotions, and targeting them appropriately for convenient services would be beneficial. After doing a brief survey on this field, we propose a system. The proposed method is shown in Figure 8.

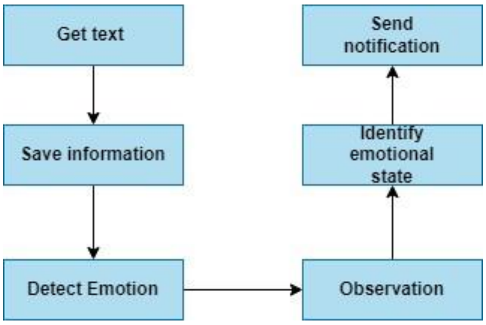


**Fig. 8.Our Propose System**

## 9. Conclusion

Detecting and understanding emotions recreate an essential role in the research on computer-human interaction. However, there is room for improvement, as many aspects of emotion detection have yet to be thoroughly analyzed. As mentioned earlier, we have already discussed different approaches to this topic. Machine learning is an automation thing that can detect emotion without human intervention. It is a continuous process to improve a system. So, by catching the lackings of a system can be developed furthermore. This survey paper will help the scholar identify the most recent techniques and approaches. Tables 2 and 3 are the most used approach. From the survey, it can be said that the combined algorithm always shows the better output, and by pointing the Fig 7, the hybrid approach is the most trending approach. This survey paper can gain a large amount of knowledge about this field and the outcome of the researchers. So the scholar can use it to get the idea, which helps us develop more in this sector.

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