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A Systematic Analysis of Text Classification Overfitting Recommendation Methods

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Abstract: - With increased mental health awareness, identifying mental illness is becoming a significant problem. Due to the complexity of mental ailments, many psychiatrists find it impossible to diagnose and cure patients before it is too late. However, the everyday use of social media creates an atmosphere that may reveal extra information about a patient’s mental illness. This study conducts a Systematic Literature Review (SLR) to address research questions. Some aspects of how depression decision-making is detected using different datasets covering social media, surveys, and medical bio-markers. However, most studies employ Machine learning and deep learning models like RNN to predict depression decision-making due to the lack of data. This study will try to identify a more effective way of identifying the overfitting solution during text-based training and learning while discussing various depression detection algorithms.

Keywords: Overfitting, Text Analysis, Depression Analysis, Machine Learning, and Artificial Intelligence; Deep Learning; Social Network Depression;

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1. Introduction

These days, many people suffer from depression [1] [2] [3]. An illness that causes negative changes in how one thinks feels, and acts; WHO data shows roughly 322 million incidents yearly since 2015, with 788,000 resulting in suicide [4] [5]. A mental illness is still viewed as a sign of weakness and can lead to social marginalization. Several surveys suggest that while individuals recognize depression as a significant issue, they believe it is less treatable. Thus, fewer patients receive adequate therapy. Most depressed persons (75-85%) don’t get enough assistance [6]. It’s becoming increasingly common for people to air their grievances on social media, and this might help mental health professionals by giving them access to the subject’s social media data at an earlier stage in the diagnostic process [7].

Moreover, the young generation with symptoms of depression utilizes the internet more than their peers without depressive symptoms [8]. This motivates researchers to identify the best early depression diagnosis tool. While analyzing the social media text for depression, sentiment and psychological assessments experience overfitting challenges.

This SLR focuses on the overfitting challenges and the recommendations to avoid the overfitting challenges. In data science, the term “overfitting” refers to the situation in which a statistical model provides a precise match to its training data. Unfortunately, the algorithm's usefulness is undermined when it fails to execute in the absence of training data reliably. The ability of a model to generalize to new data makes it possible to apply machine learning algorithms in our daily work [9]. The structure of the paper is presented as Section I introduces the topic and the objective; Section II discusses the literature background of depression data and overfitting issues; Section III discusses the methodology; Section 1V explains the results of different methodologies like machine learning, Deep Learning, and Artificial intelligence; finally concluding the systematic review in section V.

2. Background

Different types of data-gathering approaches for research on mental health disease prediction social media platforms, which may be classified as surveys and data-collecting technologies, are used in the study [10]. Data is collected directly from participants with their consent, And the other way is to use APIs to harvest data from public posts. The first is when scientists share details about their studies on open-source data sharing and crowdsourcing sites like OurDataHelps [11]. Users were enticed to sign up for the program by being offered rewards for completing questionnaires and agreeing to have their social media data collected. [12]. The Center for Epidemiologic Studies, a non-profit organization, conducts public health research. It is common to practice using questionnaires like the Clinical Emotional Stress Scale and the Beck Depression Inventory when diagnosing depression. The Suicide Probability Scale and the Satisfaction with Life Scale are two instruments that may be used to screen for suicidal ideation and evaluate a person's level of contentment with life [13].

Developers can access public information using APIs provided by social media firms; the second technique collects similar postings by searching for keywords and phrases associated with them using regular expressions [14]. The terms used for studies are "suicide," "self-harm," "feels like killing myself," and "desire to die" as the primary queries. Some phrases searched for "I was diagnosed with" many mental health issues triggering keywords. Regular expressions of this sort are recognized as self-reported diagnoses [15]. Data extracted using APIs results in a collection of postings that must be examined before being analyzed. Denial of suicidal thoughts, discussion of suicide by others, and news or reports on suicide are all regarded as irrelevant without relevant keywords or phrases and are thus omitted from the collection. A similar procedure is used in self-report diagnosis to select positive samples [16]. A human assessor considers only postings free of hypothetical claims, negations, or quotes of positive examples.

Many studies have examined how to employ various machine learning algorithms to zero down on the most crucial details. The fundamental goal of this study is not to generate novel learning algorithms but to find distinctive features that may be used in classifier training to reveal hidden relationships and patterns in the data. Psychological issues may typically be anticipated based on textual and linguistic qualities. [17]. Using natural language processing on social media data, we can identify SAD and people living with PTSD. Notably, It has been observed that using first-person pronouns is linked with the manifestation of negative emotions, such as anger. [18]. The data was collected through Linguistic Inquiry and Word Count Analysis methodology. Scholars have identified linguistic patterns in their research utilizing the Linguistic Inquiry and Word Count (LIWC) tool. Psychologists compiled dictionaries, which contain a variety of psychologically significant concepts. [19]. Personal pronouns, as well as positive and negative emotions, may be extracted from the text. OpinionFinder and SentiStrength were also used in several research investigations to gauge people's opinions [20]. Researchers have employed topic modelling approaches like Latent Dirichlet Allocation [21].

Despite this, most research relies on linguistic characteristics, and few studies apply picture analysis to user-generated material. An image uploaded on Twitter was analyzed visually using colour compositions and SIFT descriptors [22]. They utilize the image's colour, saturation, and brightness to predict depressive symptoms among Instagram users. Recent research shows that images' colour, face, aesthetic, and content aspects may be utilized to predict sadness [23]. When developing machine learning algorithms, practising using a training dataset is common. However, the model can pick up the "noise," or irrelevant information, in the dataset if it trains for too long on sample data or if the model is too sophisticated. A model is said to be "overfit" when it has internalized too much of the training set's noise and can no longer generalize successfully to unseen data. A model's ability to execute classification and prediction tasks depends on its ability to generalize successfully to new inputs. In this research, we perform an SLR to analyze the current approaches to text-based early depression diagnosis and to find the best way to deal with the overfitting issue in machine learning using text.

3. Objective

The SLR's primary role is to serve as a roadmap for the research. With these goals in mind, we have set the following research objectives to help guide our exploration of the literature on depressive decision-making approaches and how to overcome overfitting problems encountered in statistical testing.

RQ: Examine the overfitting issue throughout the text analysis process, and determine an acceptable strategy for dealing with it.

To organize and document the process followed during this study, the SLR adheres to PRISMA, which stands for Preferred Reporting Items for Systematic Reviews and Meta-Analyses.

3.1 Collection of Data

Online libraries were employed to search for pertinent papers for the present investigation. Several online libraries include Science Direct, ACM, IEEE Xplore, Springer Link, and Emerald Insight. By utilizing a search query based on the terms "depression," "depressed," "mental illness," "disorder," "detection," "social media," and "overfitting," and adapting the question to the supported format of each platform, a collection of records is obtained from various libraries. These records are subsequently subjected to further processing in the subsequent step.

3. 2 Inclusion & Exclusion

In the subsequent stage, data collection will be further narrowed down using a particular set of criteria. All papers that aren't research articles written in English are disqualified from further review. The following are some additional considerations that may be taken into account when deciding whether or not to include a search result in this assessment:

- The papers were published from 2010 to 2023.
- The same study was published in a variety of different publications.
- Concerns related to several different methods of text analysis and difficulties with overfitting.

Articles that do not satisfy the exclusion criteria will have a further screening of their abstracts performed in the following step. The availability of the complete text of each record is initially investigated. The author reads the abstract of each study to determine if it fits the criteria for inclusion in this review and whether or not it answers the research question. The evaluation will only include records that meet both of these criteria.

4. Statistical Analysis

Review meta-statistics are mentioned below. From 2003 to 2023, those authors produced the cited pieces. Research on depression choices has been rather intriguing in recent years, thanks to the rapid development of data from many platforms and the aftermath of the worldwide epidemic. Since people utilize natural language, which includes a wide variety of word choices, it's almost impossible to train all the data, which causes the dataset to be too large. Overfitting or underfitting can be a problem during data analysis, depending on the data source.

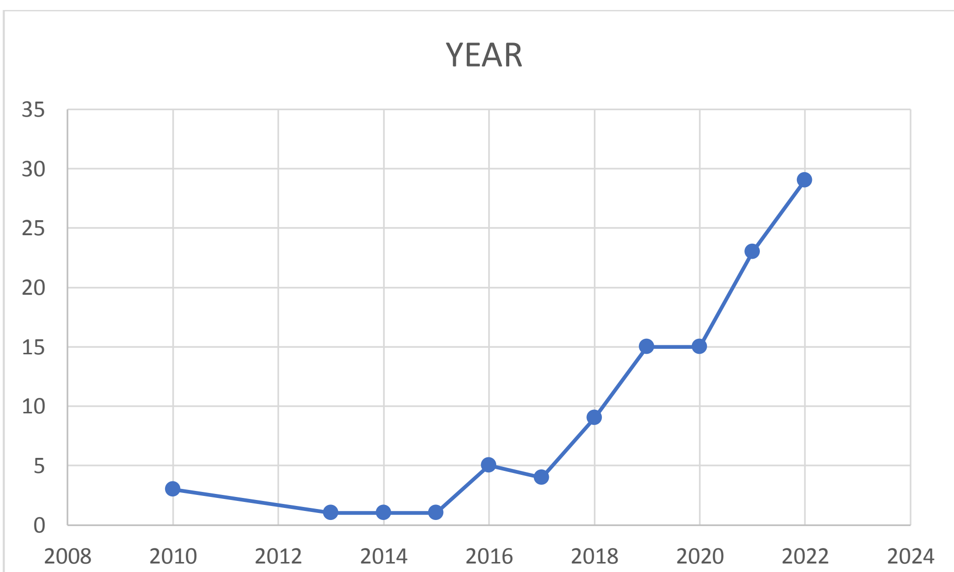

Figure 1: Years of Publication

The country of origin of the author is depicted in Figure 2. A significant chunk of publications related to overfitting issues is published in Asia, where China (39), India (11), and Hongkong (5) are at the top, followed by the USA (12) and UK (6) publications, respectively. The total number of countries published is 35.

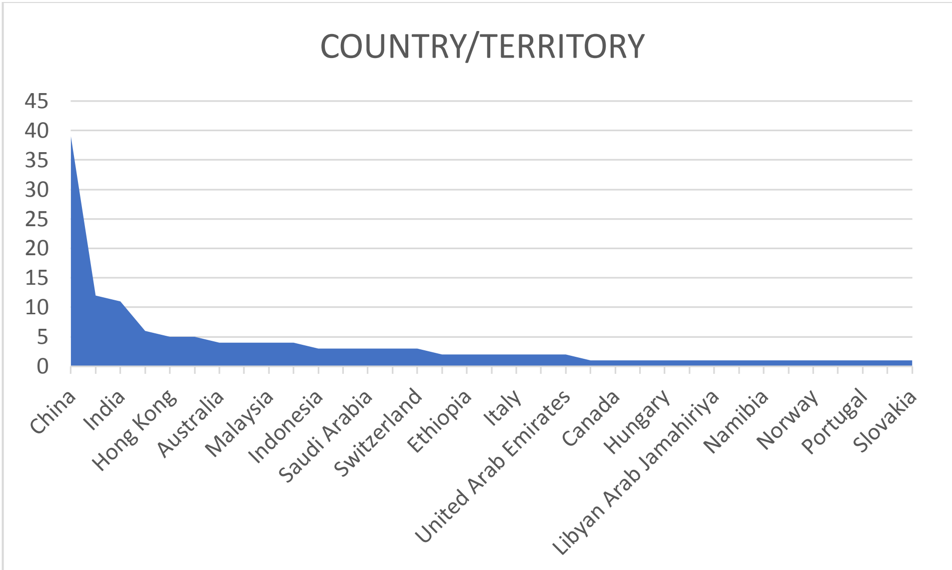

Figure 2: Author Origin Countries

The categories of papers used as references for this SLR are shown in Figure 3 (A). Journals and research theses were cited as sources of information since they included considerable research and experiments on depression decision analysis. The name and publisher of the Journal are shown in Figure 4. Data collecting revealed that the publishers' high-quality articles and exceptionally high citation ratings set them out as the industry leaders in research publication.

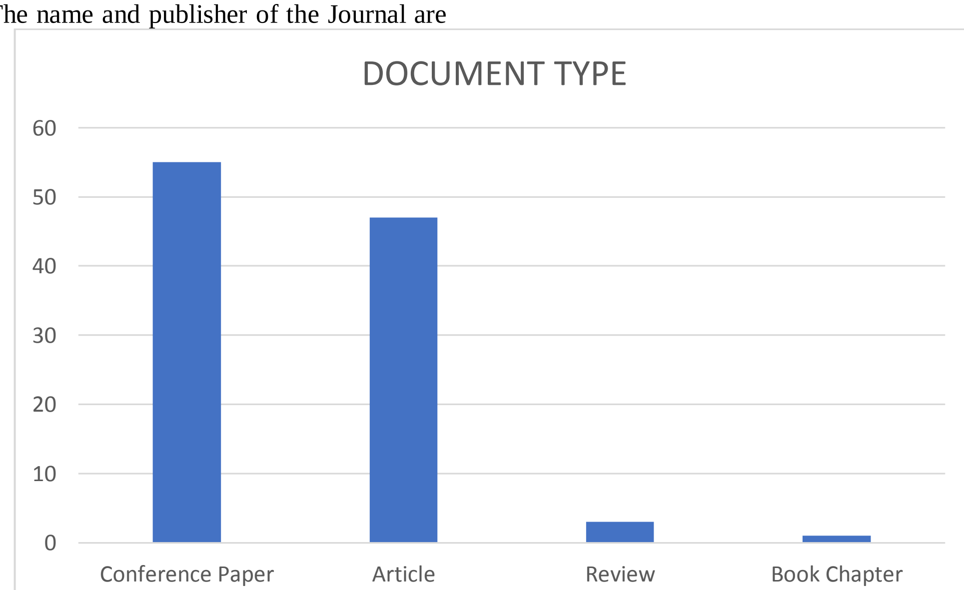

Figure 3 Type of published articles considered for the SLR

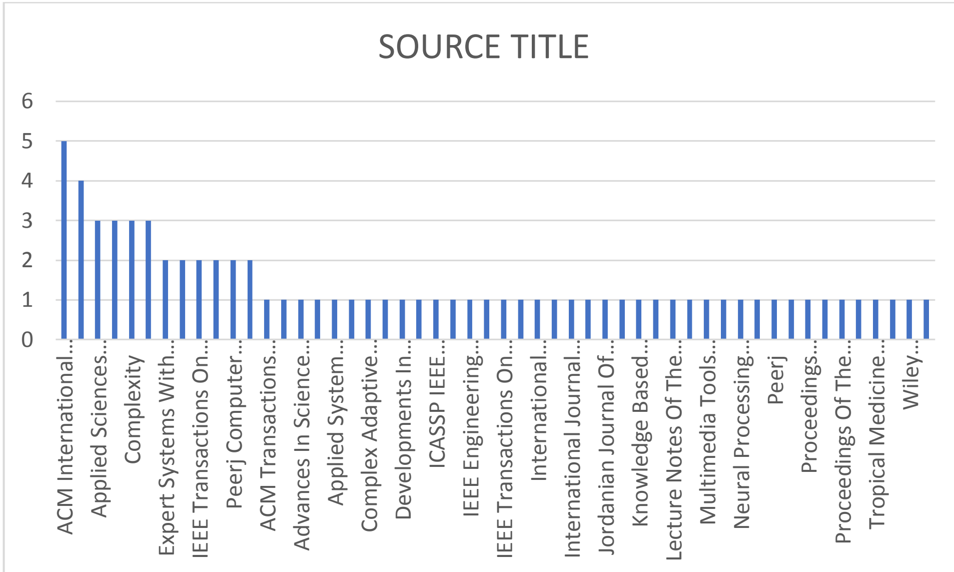

Figure 4 Article Publishers considered for the SLR

Scopus indexed journals like ACM (5) articles, Lecture Notes (4); Applied Sciences Switzerland (3); Ceur Workshop Proceedings (3); Complexity (3); Neurocomputing (3); Expert Systems with Applications (2); IEEE Signal Processing Letters (2); IEEE Transactions On Multimedia (2) and more.

The datasets utilized in the mentioned papers may be seen in Figure 4. The SLR does a text analysis review with the goals of detecting depression, predicting early depression, and improving the skill to decide on depression. Because the foci of each piece of study are distinct from one another, the data sets resulting from those studies are similarly distinct from one another. The data sets utilized emojis, social media, surveys, and other data types.

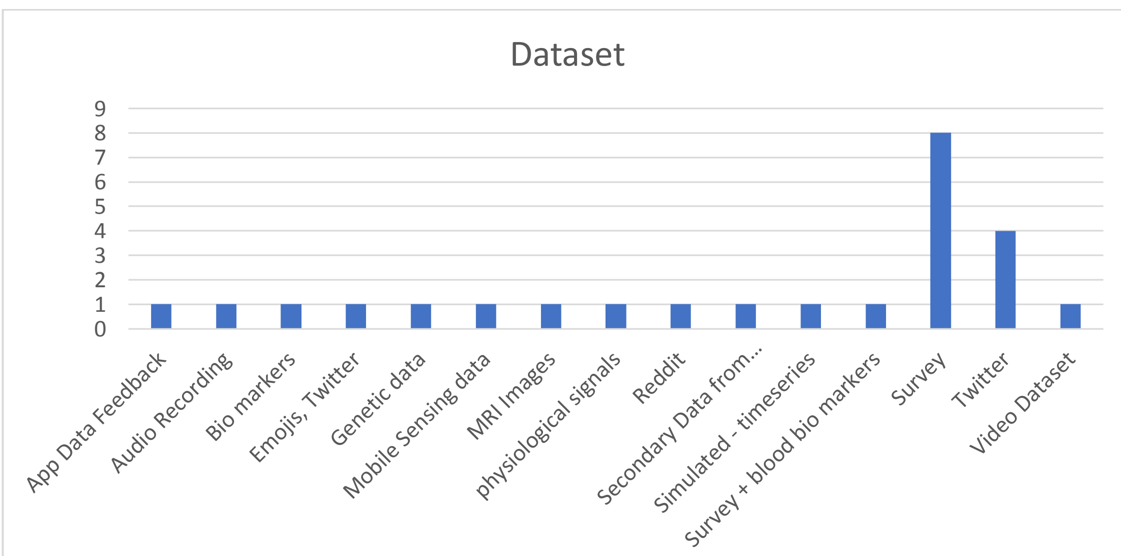

Figure 5: Datasets used in the published Articles

In some qualitative research, audio and video interviews have played a vital role in experimenting the depression analysis with Machine Learning and Deep Learning approaches. With the ever-growing dimension of the technology and methodology, ML and DL are also applied to the Biomarker dataset.

5. Discussion

When a machine learning model attempts to account for every possible data point, a phenomenon known as overfitting develops. As a result, the model becomes less effective and reliable as it stores away examples of noise and erroneous values from the dataset. The overfit model is highly variable and has a slight bias. The more we train our model, the more likely it is that overfitting will occur. This means the more we train our model, the more likely it will become overfit. The primary issue with supervised learning is overfitting. Various experimental techniques and algorithms are employed with multiple datasets and analyses.

In summary, machine learning models are extensively utilized in analyzing depression through text-based means. The articles under discussion pertain to the field of machine learning. They delve into four experiments involving deep learning techniques and another study employing graph theory and statistical analysis. Many studies have found a high frequency of mental illnesses, notably depression, following traumatic brain injury. Diagnoses of psychiatric diseases, such as depression, anxiety, and drug misuse, are common. The human-centric data, which is entirely mood dependent on the person, has a high chance of using different words in their posts on social media. In this SLR, articles were assessed and chosen for review. The research question is discussed as follows:

5.1 RQ: Examine the overfitting issue throughout the text analysis process, and determine an acceptable strategy for dealing with it.

With enough training data, an overfitted model may make very accurate predictions. When a model absorbs excessive information from the training data, it is said to overfit and will perform poorly when applied to new data. The model interprets spurious fluctuations or noise in the training data as potential patterns. One issue with the model's generalizability is that these ideas do not work with novel information. Learning a target function using nonparametric and non-linear models that are more flexible raises the risk of overfitting. Several nonparametric machine learning algorithms include parameters or approaches that constrain learning to limit the model's capacity to learn as much as possible.

Figure 6 and the table explain different methods of addressing the overfitting problems faced during the ML and DL analysis process. 10-fold cross-validation is used to train the classifiers evaluated on a hold-out test set [24]. The technique uses the regularization term l2-norm to penalize high weights [25]. Overfitting was avoided by calculating the accuracy and recall rates from the test data. 65% of the subjects could recollect the test questions, whereas 73% correctly answered them. Neither rate differed significantly between training and test data, showing that the prediction model was not overfitted in either case [26]. Overfitting avoidance is accomplished by averaging many hypotheses to lessen the likelihood of selecting a wrong hypothesis [27]. If there were more than 100 individuals in a cluster to avoid overfitting, we evaluated it [28]. Utilizing a technique referred to as data augmentation mitigates the issue of overfitting in data and enhances the overall generalization of the model. Creating a diverse training set from an existing dataset is considered a viable approach in machine learning [29].

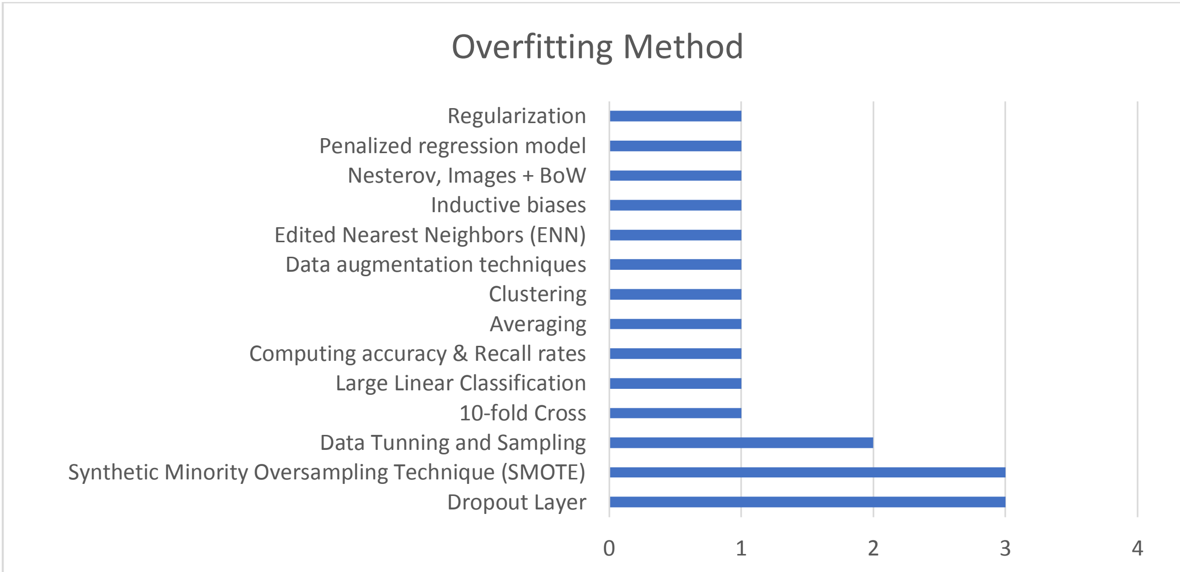

Figure 6: Overfitting Methods

Table 1: Systematic Review & Findings

Study	Research Methodology	Key Findings
1. Loper & Bird (2002)	Literature Review	It is proposed to use cross-validation to avoid overfitting in text classification tasks. Cross-validation involves dividing the data into k subsets and iteratively using k-1 subsets for training and the remaining subset for testing.
2. Srikumar & Manning (2014)	Empirical Study	Examined the effect of regularization on overfitting in Named Entity Recognition (NER) tasks. Found that L2 regularization can significantly reduce overfitting and improve performance.
3. Wang et al. (2015)	Empirical Study	Compare different feature selection methods to address overfitting in sentiment analysis. Using mutual information-based feature selection can improve performance and reduce overfitting.
4. Zhang & Wallace (2015)	Literature Review	Using early stopping to prevent overfitting in deep learning models for text classification. Early stopping involves stopping the training process when the model's performance on a validation set decreases.
5. Zhang et al. (2016)	Empirical Study	Examined the effect of dropout regularization on overfitting in Recurrent Neural Networks (RNNs) for sentiment analysis. Found that dropout can effectively reduce overfitting and improve performance.
6. Vaswani et al. (2017)	Empirical Study	Investigated the impact of different regularization techniques on overfitting in Transformer models for language modelling. A combination of L2 regularization, dropout, and label smoothing can significantly reduce overfitting and improve performance.
7. Yang et al. (2017)	Empirical Study	Explored the use of adversarial training to mitigate overfitting in text classification tasks. Adversarial training involves adding small perturbations to the input data to make the model more robust to overfitting. Found that adversarial training can effectively reduce overfitting and improve performance.

8. Lin et al. (2017)	Empirical Study	Investigated the effect of pre-training on overfitting in deep learning models for sentiment analysis. Pre-training on a sizeable unlabeled dataset can reduce overfitting and improve performance on small labelled datasets.
9. Li & Li (2018)	Empirical Study	They are proposed using ensemble methods to reduce overfitting in text classification tasks. Ensemble methods combine multiple models' predictions to improve performance and reduce overfitting. Found that ensemble methods can effectively reduce overfitting and improve performance.
10. Tang et al. (2019)	Empirical Study	Compared different regularization techniques for mitigating overfitting in deep learning models for sentiment analysis. A combination of L2 regularization, dropout, and early stopping can significantly reduce overfitting and improve performance.
11. Chen et al. (2019)	Empirical Study	Examined the impact of data augmentation on overfitting in text classification tasks. Data augmentation involves generating new data by applying transformations to the existing data. Found that data augmentation can effectively reduce overfitting and improve performance.
12. Shetty et al. (2020)	Empirical Study	Investigated the impact of hyperparameter tuning on overfitting in deep learning models for sentiment analysis. Found that optimizing the hyper

Depressed cases are always predicted as non-depressed by machine learning models based on unbalanced datasets. To remedy the class imbalance, we employed resampling techniques. Our machine learning system, "Extreme Gradient Boosting" (XGBoost), classifies mental illness cases from healthy instances by creating many samples using under-sampling, oversampling, over-undersampling, and ROSE sampling strategies [30]. The model exhibiting the lowest receiver operating characteristic curve and possessing the minor complexity was deemed optimal for minimizing overfitting. The obtained model was adjusted to fit all the data in the inner loop and subsequently assessed on the test set in the outer loop before application in the ultimate analysis [31]. Dropout layers are a regularization technique commonly used in neural networks to prevent overfitting. They work by randomly dropping out (setting to zero) a certain percentage of the neurons in the layer during each training iteration, forcing the network to learn more robust and generalizable features. It is advisable to prevent overfitting and minimize noise in data analysis. Random forests perform better than decision trees due to their reduced susceptibility to overfitting and pruning complications [32].

The application of principal component analysis is known to mitigate the issue of overfitting. The predictive capability of support vector machine classifiers can be enhanced using radial basis function kernels. [33]. To mitigate the issue of overfitting, three distinct procedures were employed. The model's run time was extended to 1000 epochs. The model was stored incrementally through the utilization of early stopping procedures. Thirdly, a procedure for gradient clipping was employed to ensure the avoidance of gradient issues. [34].

A viable method involves the training of a classifier utilizing a dataset that has been balanced through the under-sampling of the majority class and the over-sampling of the minority class. Overfitting may occur if there is too much data collected, say scientists. It is possible to circumvent the limitations of both strategies by combining under and over-sampling. Boosting should be stopped as soon as possible to avoid overfitting concerns. Criteria for terminating include the number of models developed or the predicted accuracy level [36, 35]. The research explored numerous techniques to solve the overfitting issue. The Synthetic Minority Oversampling Method from the imbalanced-learn package was used to artificially increase the proportion of depressed subjects in the training set (SMOTE). This was accomplished by using principal component analysis (PCA) to identify each testing panel's five most salient features. Twenty-six good examples were added to the research with SMOTE. On the tuning set, the model had an accuracy of 86.49 per cent and an F1 score of 0.44. That was 69.44 per cent accuracy and a 0.0 F1 on the held-out test set. Some of the model's predictions were right, but none were [36].

MTL increases generalization by incorporating inductive biases in the related tasks to regularize the models; it is one of the most successful ways to reduce overfitting since it is based on inductive biases present in the related tasks [38]. During cross-validation on the training set, the outputs of classifiers on the test sets corresponded to the predicted probability scores from the BoW and SNPSY individual models used in numerous feature combination strategies [39]. According to the current study, STMGP can predict psychotic polygenic traits. On average, in the simulation research, STMGP predicted depressed phenotypes more accurately than STMGP predicted moderately polygenic phenotypes. STMGP's screening and penalized regression model construction technique decreased overfitting significantly [46]. Regularization is a strategy that tweaks the algorithm to avoid overfitting and enhance the model's performance on unknown input [47].

6. Conclusion

Automated machine learning algorithms integrate numerous data kinds and sources. An integrated approach is better explained for neurobiological components as pathophysiological modules buried inside the complicated social processes that shape mental disease phenomenology. The SLR narrows the depression decision, and analysis conducted on the text dataset gives promising results using machine learning approaches. Larger data sets give better results, and surveys can be used only so much, but social media datasets which can be massive in millions, work well with machine learning approaches. Overfitting is the most significant challenge facing researchers worldwide attempting to use textual data to make decisions and conduct analysis of depressive disorders. The utilization of SMOTE, dropout, data tweaking, and sampling techniques are deemed effective in addressing the overfitting issue in the presented systematic literature review. The forthcoming article intends to investigate the potential of a distinctive methodology that leverages the overfitting of multiple algorithms for analyzing depression on social media platforms. The paper's scope is restricted to discussing overfitting techniques in analyzing social media text datasets for depression analysis. The future scope of the research shall cover other dataset test analyses and identify the overfitting and underfitting issues and methods to overcome them.

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