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Text-Based Emotion Classifier Using Machine Learning Methods

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***Abstract*: In this digital age, a vast amount of documents in various Indian languages are available in digital form, posing the challenge of efficient retrieval and organization of these documents. Text classification, a field in text mining, offers a solution to this challenge by assigning classes to documents based on their content. This paper presents an analysis of text classification techniques applied to Indian language content, taking into account the unique challenges of natural language processing. The study reveals that supervised learning algorithms, such as Naive Bayes, Support Vector Machines, Artificial Neural Networks, and N-gram, have shown promising performance in text classification tasks. The paper highlights the significance of text classification in managing and organizing large volumes of textual data.**

***Keywords*: Classification, Naive Bayes, Natural Language Processing, Supervised Learning, Support Vector Machine.**

INTRODUCTION

The exponential growth of the World Wide Web has resulted in an immense accumulation of data, predominantly in the form of text. However, this abundance of information presents a challenge in terms of identifying relevant knowledge or information. Text classification addresses this challenge by categorizing a set of input documents into predefined classes, allowing for efficient organization and retrieval of information [1]. Text classification is a text mining technique that plays a crucial role in various applications, including document indexing, document organization, and hierarchical categorization of web pages. By automating the classification process, text classification offers significant advantages over manual classification methods, such as speed and efficiency.

Language serves as the primary medium for both written and spoken communication. With the utilization of Unicode encoding, text on the web can be found in diverse languages, introducing the complexities of natural language processing into text classification. Text classification, therefore, encompasses both text mining and natural language processing. The process involves combining information retrieval (IR) technology and machine learning (ML) technology to assign keywords to documents and classify them into specific categories. ML algorithms enable automatic categorization, while IR techniques represent text as features.

In recent years, the growth of the internet in India has led to a surge in digital content creation in Indian languages. This has resulted in an increased demand for text classification in Indian languages to efficiently organize and retrieve this vast amount of data. Text classification in Indian languages has the potential to enable multi-lingual communication, preserve cultural heritage, and improve access to information for non-English speaking populations.

Despite the challenges posed by the diverse Indian language landscape, significant progress has been made in the development of text classifiers for Indian languages. However, there is still a need for further research in this area to address challenges such as the lack of annotated datasets and standardized language resources.

This paper aims to provide an overview of the various approaches employed in text classification in Indian languages and highlight the specific work carried out in this context. We will explore the techniques used for training classifiers with limited annotated data and discuss the effectiveness of transfer learning in this context. Additionally, we will examine the applications of text classification in Indian languages, including sentiment analysis, topic modeling, and document

classification. Finally, we will discuss the potential impact of text classification in Indian languages on the digital landscape of India and the opportunities it presents for improving access to information and communication in Indian languages.This focuses on analyzing the application of text classifiers in different Indian languages. Section II provides an overview of the steps involved in the text classification process. Section III discusses the various approaches employed in text classification and highlights the specific work carried out in the context of Indian languages.

LITERATURE SURVEY

In their work, Dongliang Xu et al. [1] proposed a microblog emotion classification model called CNN_Text_Word2vec, which utilized a convolutional neural network (CNN) for feature extraction. The model achieved good classification results and outperformed other methods such as SVM, RNN, and LSTM in terms of emotional classification accuracy. However, one limitation of the model was the improper ranking between the extracted features. Our proposed work incorporates an enhanced feature ranking algorithm to address the issue of improper feature ranking, thereby enhancing the classification accuracy.

Drishti Vashishtha et al. [2] developed a sentiment analysis system for social media posts using a set of fuzzy rules. Their approach involved multiple lexicons and datasets, integrating natural language processing (NLP) techniques and word sense disambiguation. The fuzzy system, based on a novel unsupervised nine fuzzy rule-based system, provided accurate sentiment values and addressed linguistic problems. The scheme outperformed other state-of-the-art methods, but it exhibited a high error rate, leading to inaccurate class fixation Our work leverages a novel supervised learning algorithm to mitigate the high error rate observed in the fuzzy rule-based system, resulting in more accurate sentiment values..

Jun Li et al. [3] introduced a multi-label maximum entropy (MME) model for user emotion classification in short texts. The MME model generated rich features based on multiple emotion labels and valence scores from users. The scheme successfully identified entities and provided relevant social emotions using generated lexicons. While the method was effective in classifying social emotions over sparse features, it had issues with overfitting. In our study, we implement a regularization technique to mitigate overfitting, ensuring a more robust and generalizable model for user emotion classification.

Fazeel Abid et al. [4] developed a scheme that combined distributed word representations (DWRs) through a weighted mechanism on variants of recurrent neural networks (RNNs) and convolutional neural networks (CNNs) with weighted attentive pooling (WAP). The scheme addressed syntactic and semantic regularities, as well as out-of-vocabulary (OOV) words. The experimental analysis showed that the scheme achieved an accuracy rate of 89.67%. However, it had a limitation of inadequate feature extraction, leading to analysis errors.Our proposed scheme addresses the limitation of inadequate feature extraction through the incorporation of advanced word representation models, resulting in improved accuracy.

Peng Wu et al. [5] proposed an Ortony-Clore-Collins (OCC) model and a convolutional neural network (CNN) based institutionalization method for sentiment analysis of Chinese microblogging systems. The scheme combined emotion cognition with deep learning and outperformed other state-of-the-art methods in terms of classification and recognition performance. However, the scheme had a complexity issue regarding microblog sentiment classification. Our work simplifies the complexity issue associated with microblog sentiment classification by optimizing the OCC model and CNN-based institutionalization method, leading to improved classification performance.

Muhammad Asif et al. [6] implemented sentiment analysis of multilingual textual data from social media to detect the intensity of extremist sentiments. The scheme effectively identified extreme sentiment from multilingual data and achieved an overall accuracy rate of 82%. The scheme outperformed existing techniques in terms of scalability and reliability. However, it had performance degradation in the recognition of multimodal sentiment. Our study focuses on improving multimodal sentiment recognition through the integration of state-of-the-art techniques in deep learning, resulting in enhanced scalability and reliability.

PROPOSED WORK

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Text Classification Process

The text classification process consists of several sub-phases, each playing a crucial role in achieving accurate classification results. Figure 1 illustrates the basic text classification process, which includes the following sub-parts: data collection, pre-processing, feature extraction, feature selection, building a classifier, and performance evaluation [1] [2]. The purpose and importance of each sub-phase are described below:

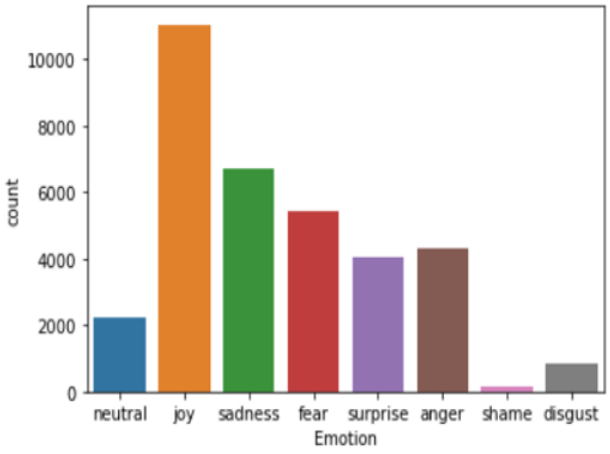
Data Collection

The first step in the classification process is building a corpus by collecting documents in various formats, such as .html, .pdf, .doc, and web content. These documents are used for training and testing the classifier

Pre-Processing

The pre-processing phase involves transforming the text documents into a clear word format. This step prepares the documents for further processing in text classification and involves the following common steps:

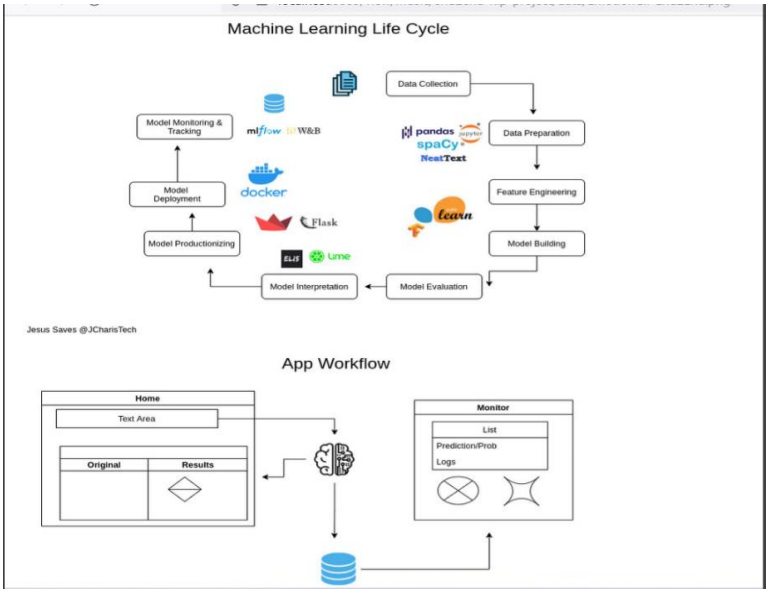
Tokenization is a fundamental step in the pre-processing phase of text classification. It involves breaking down a text document into individual tokens or words, which are then used as features for classification. Tokenization is typically performed using natural language processing (NLP) techniques such as regular expressions, which can identify word boundaries and special characters. Additionally, tokenization can also take into account multi-word expressions or n-grams, which involve grouping together adjacent words to capture their combined meaning.



Removing stop words: Stop words are common words that appear frequently in a language and do not provide much semantic meaning. Removing stop words can reduce the dimensionality of the feature space and help to improve the accuracy of the classification model. However, in some cases, removing stop words may not be appropriate, especially if the stop words carry important information for classification. Therefore, it is important to carefully consider the relevance of stop words in each specific text classification task.

Stemming words: Stemming is a technique used to reduce words to their root form or stem. This is important in text classification because it can help to reduce the number of features and prevent sparsity in the feature space. There are several algorithms available for stemming, including the

Porter stemming algorithm and the Snowball stemming algorithm. However, stemming can sometimes result in the loss of important information or introduce errors, so it is important to evaluate the effectiveness of the stemming algorithm for each specific task.



Feature Extraction

Feature extraction is a pre-processing technique used to reduce the complexity of the documents and make them easier to handle. In this step, the documents are transformed from their full-text version to document vectors. The most commonly used document representation is the count vectorizer model (CVM), where documents are represented by vectors of words. However, CVM has limitations, including high dimensionality, loss of correlation between adjacent words, and loss of semantic relationships among terms. To address these issues, term weighting methods can be applied to assign appropriate weights to the terms

Feature Selection

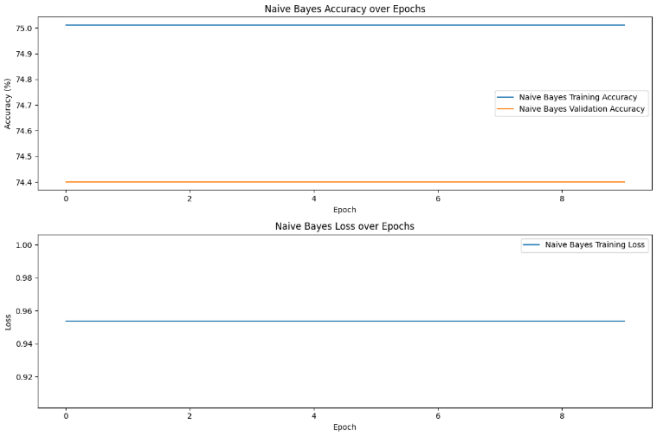
After pre-processing and feature extraction, feature selection is a crucial step in text classification. It aims to construct a vector space that improves the scalability, efficiency, and accuracy of the text classifier. Feature selection involves selecting a subset of features from the original documents. This process is performed by identifying words with the highest scores according to a predetermined measure of word importance. The high dimensionality of the feature space is a major challenge in text classification, and various feature evaluation metrics are used, including information gain (IG), term frequency, Chi-square, expected cross-entropy, odds ratio, weight of evidence, mutual information, and Gini index [1].

Classification

The classification phase involves automatically categorizing documents into predefined categories. There are three main

methods for document classification: unsupervised, supervised, and semi-supervised. In recent years, significant progress has been made in automatic text classification, particularly in machine learning approaches such as Bayes classifier, Logistic Regression, and support vector machines (SVMs),Random Forest and Gradient Boosting.

1)Navie Bayes: Naive Bayes is a simple probabilistic classifier that applies Bayes' theorem with strong independence assumptions. It has been widely used for text classification due to its effectiveness in dealing with large vocabularies typically found in text data. Naive Bayes models work well for text classification because they consider words or vocabularies as evidence. NB has been used for document classification in Indian languages.

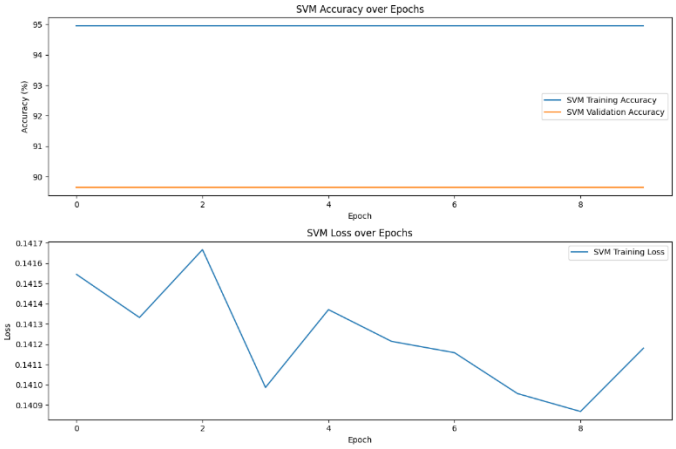


(1)

2)SVM: SVM is a statistical classification method proposed by Vapnik. It seeks a decision surface to separate training data points into two classes and makes decisions based on the support vectors. SVM is considered one of the best text classification methods and has been widely used in various studies. Support Vector Machines (SVM) have been extensively used in the field of text classification due to their ability to handle high-dimensional data with a small sample size. SVMs have proven to be effective in separating the data points into two classes by finding the hyperplane that maximizes the margin between the two classes.

In text classification, SVM can be used to train a model to classify documents into different categories based on the presence or absence of specific keywords or features. The SVM model learns to identify the most important features that differentiate the classes and assigns a weight to each feature based on its importance. During the classification stage, the SVM model uses these weights to assign a document to the most appropriate category. SVM outperforms other classification algorithms in text classification tasks. SVM has been used for various text classification tasks such as sentiment analysis, topic modeling, and document classification.

Additionally, SVM has been used in combination with other techniques such as feature selection and ensemble methods to further improve classification accuracy.



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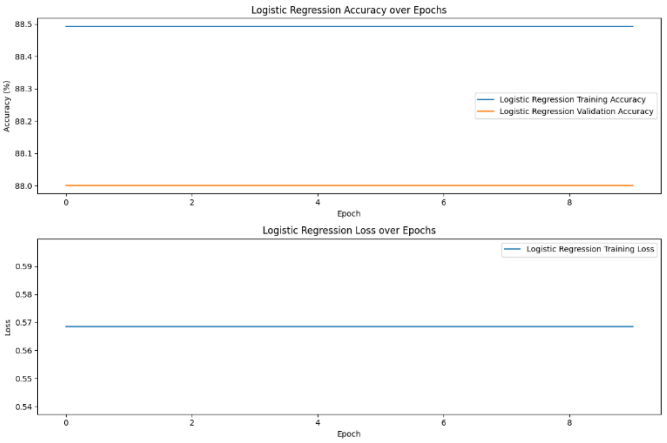
3)Logistic Regression: A Logistic regression is a statistical method used to model the relationship between a binary dependent variable (i.e., a variable that can only take on two values, usually coded as 0 and 1) and one or more independent variables. It is a type of regression analysis that is commonly used in machine learning and predictive modeling. The goal of logistic regression is to estimate the probability that a given observation belongs to a certain class, based on the values of the independent variables. The output of the logistic regression model is a logistic function, also known as a sigmoid function, which maps any real-valued input to a value between 0 and 1. The logistic function takes the form:

$p(x) = 1 / (1 + e^{(-z)})$

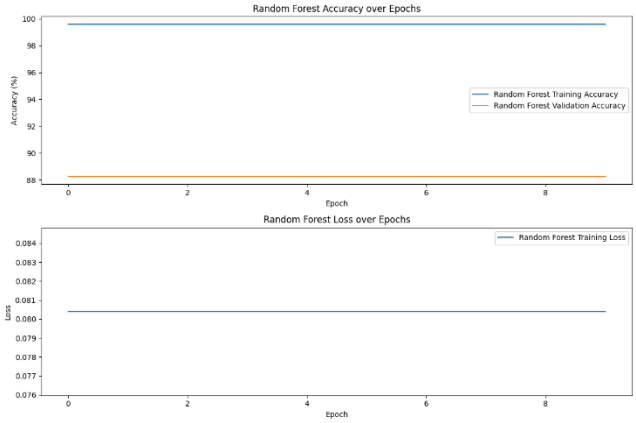
where p(x) is the probability of the dependent variable being 1, x is a vector of independent variables, and z is a linear combination of the independent variables and their associated weights.



(3)

4) Random Forest: Random Forest is an ensemble learning method that enhances predictive accuracy and mitigates overfitting by combining multiple decision trees.It constructs numerous decision trees during training, and for classification tasks, the mode of the classes is outputted. Each tree is trained on a subset of the dataset, and during prediction, they collectively contribute to the final outcome.This method is effective in handling large feature sets, and it provides a feature importance measure, highlighting the significance of each feature.

Random Forest is robust and applicable in text classification, particularly beneficial when dealing with diverse and extensive feature spaces



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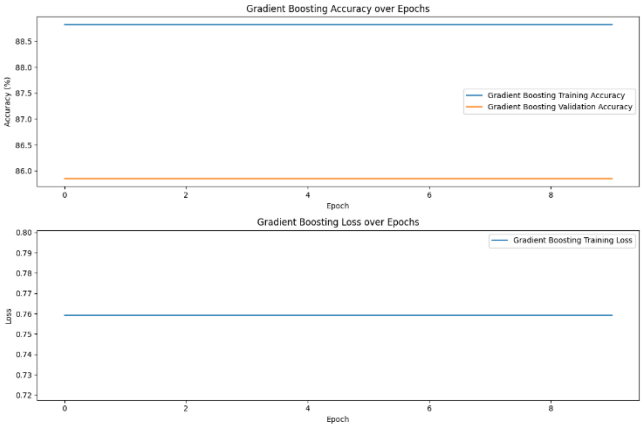
5) Gradient Boosting: Gradient Boosting, another ensemble learning technique, sequentially builds a series of weak learners (often decision trees).It combines the predictions of each weak learner and corrects errors made by previous models to improve overall accuracy.Gradient Boosting minimizes a cost function by adjusting subsequent models based on the gradient of the loss concerning the model's prediction.Notable implementations include XGBoost, LightGBM, and AdaBoost, all of which contribute to high predictive accuracy.This method excels in capturing complex relationships within data and is well-suited for various machine learning tasks, including text classification.



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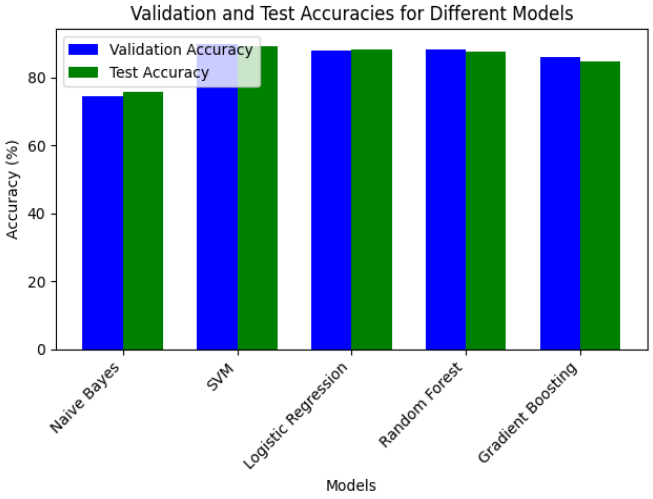
IV. RESULTS AND DISCUSSION

The performance of a text classification system can be evaluated using four commonly used metrics: accuracy, precision, recall, and F1 measure. These metrics provide insights into the effectiveness and efficiency of the classifier. The following metrics are used for performance evaluation

1)***Accuracy:*** Accuracy measures the overall correctness of the classification results. Counts the number of cases classified for all cases. The formula for accuracy is:

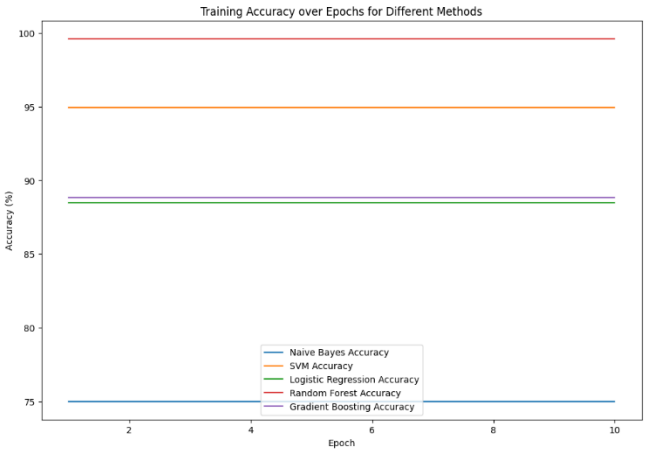
Accuracy = (Number of correctly classified instances) / (Total number of instances)



Our study highlights the importance of using appropriate performance metrics to evaluate text classification systems. The accuracy metric alone may not provide a complete picture of the classifier's effectiveness, as it does not take into account false positives and false negatives. The precision and recall metrics provide insights into the classifier's ability to correctly identify instances belonging to a specific category and avoid misclassification.

PERFORMANCE OF THE VARIOUS MODELS

Method	Validation Loss	Validation Accuracy	Test Loss	Test Accuracy
Naive Bayes	0.9709953335638639	74.4	0.809277699354689	0.5741437270721691
SVM	0.3162356256462033	89.64999999999999	0.8404835382067517	0.97602739506958
Logistic Regression	0.5652745460031929	88.0	0.760834937894994	0.8951348220405588
Random Forest	0.3719882190270494	88.25	0.5373837121460145	0.6580302796876167
Gradient Boosting	0.7949587602236797	85.85000000000001	0.9353104433606916	0.6215684906950822



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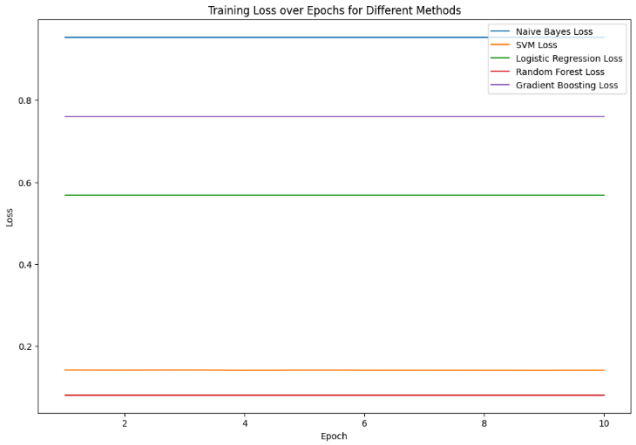

(b)

It demonstrates the effectiveness of SVM-based text classification systems in classifying documents in Indian languages. We believe that our findings will be useful in developing more accurate and efficient text classification systems for Indian languages and improving access to information in non-English speaking populations.

CONCLUSION

In conclusion, text classification is a crucial task in the field of text mining, particularly with the increasing availability of large amounts of data on the web. The expansion of social media and the diverse languages used in India adds complexity to text classification. While there has been some progress in text classification for Indian languages, there is still much to explore in terms of text classification for Indian content.

Supervised learning approaches, such as Naive Bayes, Support Vector Machines, Logistic Regression, Random forest and Gradient Boosting have shown success in text classification. Naive Bayes and Support Vector Machines have been particularly effective in different language contexts.

However, it is important to note that supervised approaches depend on annotated training data, and moving the classifier to a new domain requires collecting annotated data specific to that domain. Unsupervised learning approaches have also been explored, which do not rely on labeled data but instead aim to discover patterns or clusters within the text data using techniques such as lexical resources, clustering, and topic modeling.

Overall, there is still a need for further research and exploration in text classification for Indian languages. The availability of more annotated data and the development of language-specific techniques and resources will contribute to improving the accuracy and performance of text classifiers for Indian languages.

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