IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

ENHANCING MULTI-CLASS TEXT CLASSIFICATION IN IMBALANCED NEWS DATA

Mr.N.M.K. Ramalingam Sakthivelan[1], Arunkumar.A[2], Atthish.P[3], Kishore Kumar.AL[4]
[1]*Associate professor,* [2] *student,* [3] *student,* [4] *student*
Department of Computer Science and Engineering,Paavai Engineering College (Autonomous)
Pachal, Namakkal, Tamil Nadu., India.

***Abstract**: With the increasing amount of information or data stored in electronic format there is a need for powerful means for the analysis and interpretation of such data which could be useful in the decision-making process. The last few years have seen a growth of research interest in the development of textual data management techniques in this era of information, news is accessible very easily as news is available through online sources. This becomes a necessity to classify such data as news articles pose a great influence on various sections of our lives. This project presents a system for the classification of news articles based on text mining and deep learning algorithms such as Natural language processing and Multilayer perceptron algorithm. Experimental results show that the proposed system provides improved accuracy in news classification.*

***IndexTerms* - NLP, MLP algorithm, Machine Learning, Deep Learning Technique, BERT Algorithm**

INTRODUCTION

The goal of this project News articles are typically represented as text documents. NLP techniques are employed to convert these textual data into numerical vectors, which can be understood and processed by machine learning algorithms. Common methods include bag-of words, TF-IDF (Term Frequency-Inverse Document Frequency), and word embeddings such as Word2Vecor GloVe.NLP models often extract features from the text to capture important information relevant to the classification. These features may include word frequencies, n-grams, syntactic structures, or semantic representations, depending on the complexity ofthe model and the task at hand. Various machine learning algorithms are used for news classification, ranging from traditional models like ***Naive Bayes, Support Vector Machines (SVM), and Decision Trees to more advanced techniques such as deep learning models like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer-based architectures like BERT (Bidirectional Encoder Representations from Transformers***).

Building an effective news classification model requires a substantial amount of labeled training data, where each news article is associated with its corresponding category or topic. This data is crucial for training and evaluating the performance of themodel. To assess the performance of news classification models, various evaluation metrics are used, including accuracy, precision,recall, F1-score, and confusion matrix analysis. These metrics help in understanding how well the model is performing across different categories and identifying areas for improvement classification models may need to be adapted to specific domainsor languages to achieve optimal performance. Domain adaptation techniques help in fine-tuning pre-trained models or transferringknowledge from one domain to another, thereby improving the model's effectiveness in classifying news articles accurately. With the continuous influx of news articles, real-time processing becomes essential for timely classification. Efficient algorithms and scalable infrastructure are required to handle the high volume of incoming data and classify it 2 promptly.

News classification models need to be designed and evaluated carefully to mitigate biases and ensure fairness in the classification process. Understanding the decisions made by news classification models is crucial for trust and transparency. Techniques for model interpretability, such as feature importance analysis or attention mechanisms, help in understanding which features or words contribute most to the classification decision. News classification models should be adaptable to changing trendsand evolving news topics. Continuous learning techniques allow the model to update itself over time based on new data, ensuring its relevance and accuracy in classifying news articles.

RESEARCH METHODOLOGY

[1] Ashish Bajaj, While deep learning models have shown remarkable performance in various NLP tasks, including news classification, they are not without vulnerabilities. Here are some key vulnerabilities associated with deep learning models in news classification: Deep learning models heavily rely on large volumes of labeled training data. If the training data contains biases, suchas underrepresentation or misrepresentation of certain topics or perspectives, the model may learn and perpetuate these biases, leading to skewed classifications. Deep learning models, including those used for news classification, are susceptible to adversarialattacks. Adversarial examples are crafted inputs that are intentionally designed to mislead the model's predictions. Attackers can manipulate news articles by making subtle changes that are imperceptible to humans but significantly alter the model's classificationDeep learning models are prone to overfitting, especially when trained on limited or noisy data. Overfitting occurs when the modellearns to memorize the training data instead of capturing underlying patterns and generalizing them to unseen data. In the context of the new classification, overfitting may result in poor performance when applied to new articles outside the training set. Deep learning models, particularly complex architectures like deep neural networks, often lack interpretability. It can be challenging tounderstand why a model makes a particular classification decision, making it difficult to diagnose and rectify errors or biases. Thislack of transparency can undermine trust in the model's outputs. News topics and language usage evolve over time, leading to concept drift. Deep learning models trained on historical data may struggle to adapt to these changes, resulting in degraded Biasedmodels that can perpetuate performance over time. Continuous monitoring and retraining of the model are necessary to mitigate theimpact of concept drift. While deep learning models excel at capturing intricate patterns in data, they may struggle with generalizingto diverse news sources or languages not adequately represented in the training data. Models trained on news articles from specificdomains or languages may exhibit poor performance when applied to out-of-domain or multilingual scenarios. Training deep learning models for news classification requires significant computational resources, including high-performance GPUs or TPUsand large-scale datasets. This resource intensiveness can be a barrier to entry for researchers or organizations with limited computational infrastructure or budget. Addressing these vulnerabilities requires a multi-faceted approach, including robust data collection and preprocessing techniques, adversarial training methods, regularization techniques to prevent overfitting, interpretability methods for model transparency, and ongoing model monitoring and adaptation to handle concept drift. Additionally, fostering collaboration and transparency within the NLP community can help address these challenges collectively.

[2] Shahzada Daud,… Topic classification of online news articles using optimized machine learning models involves several key steps and considerations. Here's a generalized outline of the process Gather a diverse dataset of online news articles covering various topics. Sources may include news websites, RSS feeds, or APIs. Preprocess the text data by removing noise such as HTML tags, punctuation, stop words, and special characters. Perform tokenization and lowercasing. Optionally, apply techniques like stemming or lemmatization to normalize the text. Convert the preprocessed text into numerical features that machine learning models can understand. Common techniques include TF-IDF (Term Frequency-Inverse Document Frequency), word embeddings(Word2Vec, GloVe), or pre-trained language models like BERT. Experiment with different feature representations to capture thesemantics and context of news articles effectively. Choose appropriate machine learning models for topic classification, such as Naive Bayes, Support Vector Machines (SVM), Decision Trees, Random Forests, or neural network architectures like ConvolutionalNeural Networks (CNNs) or Recurrent Neural Networks 3 (RNNs). Split the dataset into training, validation, and test sets for modelevaluation. Use techniques like cross-validation and grid search to tune hyperparameters and optimize model performance. Consider ensemble methods to combine predictions from multiple models for improved accuracy. Train the selected models on the training dataset using the optimized hyperparameters. Evaluate the models ‘performance on the validation set using appropriate evaluation metrics such as accuracy, precision, recall, F1-score, or confusion matrix analysis. Fine-tune the models based on validation resultsand iterate if necessary. Assess the models' robustness by testing them on a separate test set to measure their generalization ability. Deploy the trained model to classify new incoming news articles in real-time Implement monitoring mechanisms to track themodel's performance over time and detect any degradation or drift. Update the model periodically by retraining on fresh data to maintain its effectiveness and adapt to changing trends. Ensure that the model's predictions are interpretable and transparent, especially in critical applications where decision-making based on news classification is involved. Use techniques such as feature importance analysis, attention mechanisms, or model-agnostic interpretability methods to explain the model's reasoning behind classification decisions. By following these steps and leveraging optimized machine learning models, you can build an effective and scalable system for topic classification of online news articles, facilitating tasks such as information retrieval, content recommendation, and trend analysis.

[3] Alima Petkuvo,….The "MN DS" dataset is a multilevel news dataset specifically designed for the hierarchical classification of news articles. Here's an overview of what such a dataset might entail and why it's useful In multilevel classification, each news article can belong to multiple categories simultaneously. This contrasts with traditional single-label classification, where each articleis assigned to only one category. Hierarchical classification organizes the categories into a hierarchical structure, typically

represented as a tree or a directed acyclic graph (DAG). This allows for a more nuanced understanding of the relationships between different categories. For example, in a news classification scenario, topics like "Politics" and "Economy" might be parent categorieswith subcategories such as "Foreign Policy" and "Financial Markets" nested underneath them. The dataset consists of a collectionof news articles obtained from various sources, covering a wide range of topics and domains. Each news article is associated withmultiple labels corresponding to the categories it belongs to. These labels are organized hierarchically, with parent and child categories. The hierarchical structure of the categories reflects the relationships between different topics. For instance, broader topics like "World News" may have subcategories like "Politics," "Economy," "Health," etc. Hierarchical classification allows formore fine-grained categorization of news articles, enabling systems to capture subtle differences between related topics. By understanding the hierarchical relationships between topics, content recommendation systems can provide more relevant suggestions to users based on their interests. Analyzing the distribution of news articles across different levels of the hierarchy can provide insights into emerging trends and patterns in news coverage. Hierarchical classification facilitates more precise retrieval of news articles based on specific topics or subtopics, enhancing the effectiveness of search engines and recommendation systems. Hierarchical classification often leads to imbalanced datasets, where certain categories may have significantly fewer instances compared to others. Balancing the dataset while preserving the hierarchical structure is a challenging task. Hierarchical classification requires models capable of capturing the hierarchical relationships between categories. Designing and training suchmodels effectively can be computationally intensive and may require sophisticated architectures. Traditional evaluation metrics formultilevel classification may need to be adapted to account for the hierarchical nature of the dataset. Metrics like hierarchical precision, hierarchical recall, and F1-score are commonly used for this purpose. In summary, the "MN-DS" dataset provides a valuable resource for researchers and practitioners interested in developing and evaluating hierarchical multilevel classification models for news articles, addressing the complexities of organizing and categorizing diverse news content.

[4] Muhammad Umar,…The impact of Convolutional Neural Networks(CNNs) and Fast Text embedding on text classification is significant, offering improvements in accuracy, efficiency, and generalization. Here's a breakdown of their impacts CNNs are adept at learning hierarchical features from sequential data, making them effective for text classification tasks. They can automatically extract useful features from raw text, capturing both local and global patterns. CNNs possess translation-invariant properties, enabling them to identify patterns regardless of their position in the input sequence. This property is advantageous for text classification tasks where the position of words within the document may vary. CNNs can learn hierarchical representations oftext, capturing both low-level features (e.g., individual words) and high-level features (e.g., phrases or semantics). This hierarchicalrepresentation facilitates better understanding and classification of text data. CNNs are computationally efficient, especially when compared to recurrent neural networks (RNNs) or transformers. They can process text data in parallel, making them suitable for large-scale text classification tasks. Fast Text embedding captures sub-word information by representing words as the sum of theircharacter n-gram embeddings. This enables Fast Text to handle out-of-vocabulary words and morphologically rich languages effectively. Fast Text embeddings consider the internal structure of words, capturing morphological and semantic similarities between words. This is particularly beneficial for text classification tasks involving languages with complex morphology or wherecontext plays a crucial role. Fast Text embeddings are computationally efficient to compute and require less memory compared tomore complex embeddings like Word2Vec or GloVe. This efficiency makes them suitable for large-scale text classification tasks,especially in resource-constrained environments. Fast Text embeddings generalize well to unseen words or domains due to their ability to capture morphological similarities. This is advantageous for text classification tasks where the training data may be limited or where the vocabulary is constantly evolving. Overall, the combination of CNNs and Fast Text embedding has a profound impacton text classification tasks CNNs leverage the hierarchical features learned from Fast Text embedding, leading to improved classification accuracy. Both CNNs and Fast Text embeddings are computationally efficient, making them scalable to large datasetsand real-time applications. Fast Text embeddings enhance the robustness of CNN-based classifiers by capturing sub-word information and morphological similarities, reducing the impact of out-of-vocabulary words or linguistic variations. While CNNsmay lack interpretability due to their complex architectures, the use of Fast Text embedding provides some level of interpretability by incorporating subword information and linguistic features into the classification process. In conclusion, the combination of Convolutional Neural Networks and Fast Text embedding offers a powerful framework for text classification, leveraging the strengths of both models to achieve state-of-the-art performance across various domains and languages.

[5] Zhiying Jiang,…Developing a parameter-free text classification method suitable for low-resource environments, augmented with compressors, can significantly enhance efficiency and effectiveness. Here's an outline of such an approach Break down the text into individual tokens (words or sub-words). Convert all tokens to lowercase to ensure consistency. Eliminate common words (e.g., "the", "and", "is") that don't carry significant meaning. Stemming or Lemmatization: Reduce inflected wordsto their root form to normalize the text. Construct a vocabulary of unique words across the dataset. Represent each document as a vector of word counts or frequencies.TF-IDF (TermFrequency Inverse Document Frequency): Weight the importance of words ineach document based on their frequency across the corpus. Generate word embeddings to represent words as dense vectors capturingsemantic information. Fast Text embedding is efficient and effective for low-resource environments. Reduce the precision of

numerical values (e.g., word embeddings or model parameters) to require less memory and computational resources. Techniques like 8-bit quantization can significantly reduce model size without sacrificing performance. Identify and remove redundant or less important parameters in the model. Pruning techniques such as magnitude- based pruning or weight clustering can reduce the sizeof neural networks while preserving performance. Transfer knowledge from a larger, more complex model (teacher) to a smaller, simpler model (student). This allows for a compact representation of the decision boundaries learned by the teacher model. Utilizealgorithms specifically designed for compressing machine learning models, such as Huffman coding, arithmetic coding, or linear quantization. A simple and interpretable classifier that partitions the feature space based on thresholding features. A 5 probabilisticclassifier that assumes independence between features, making it lightweight and well-suited for low-resource environments. A linear classifier that assigns weights to features and combines them to make predictions. It has a small memory footprint and is computationally efficient. Evaluate the performance of the classification method using k-fold cross-validation to ensure robustnessand generalization. Fine-tune parameters such as regularization strength or decision thresholds to optimize performance on the validation set.Compression Ratio vs. Performance Trade-off: Experiment with different compression techniques and compressionratios to find the optimal balance between model size and classification accuracy. Deploy the parameter-free classification method with compressors in low-resource environments, such as edge devices or resource-constrained servers. Monitor the performance ofthe deployed model and periodically retrain or update the model using new data to adapt to changing conditions. By combining a parameter-free classification method with efficient feature extraction techniques and compression algorithms, it's possible to developlightweight yet effective text classification models suitable for low-resource environments. These models can be deployed in variousapplications, including mobile devices, IoT devices, or distributed systems, where computational resources are limited doing this goesthrough a complete thought process of your Journal subject and research for its viability by the following means..

PROBLEM DEFINITION

The problem at hand revolves around the efficient categorization of news articles into predefined topics or types. This entails developing a text-mining algorithm capable of several key tasks. Initially, the algorithm undertakes text preprocessing, whereby it cleanses the data by removing HTML tags, special characters, and punctuation, followed by tokenization into individual words or subwords. Additionally, common stop words are eliminated, and stemming or lemmatization techniques are applied to standardizethe words. Subsequently, the algorithm extracts keywords or phrases that are most relevant within each news article. This involves computing importance scores utilizing methods such as TFIDF, thereby identifying words that best encapsulate the article's topicor content. Furthermore, the algorithm delves into topic analysis, aiming to discern the underlying themes present in the news articles. This process typically involves measuring the similarity between words or employing more advanced techniques like wordembeddings to uncover related topics. Ultimately, by executing these tasks effectively, the text mining algorithm enables accuratecategorization of news articles, facilitating streamlined access and organization of information for users. By iteratively adjusting the model parameters during the training process, the algorithm optimizes its ability to accurately classify news articles into relevantcategories. This predictive capability enhances the utility of the text mining algorithm, providing users with efficient access to newcontent tailored to their interests or information needs. Additionally, the algorithm's performance can be further evaluated and refined through metrics such as accuracy, precision, recall, and F1- score, ensuring its effectiveness in real-world applications. Overall, by encompassing these tasks, the text mining algorithm offers a comprehensive solution for news categorization, enablingusers to navigate and consume news content more effectively.

OVERVIEW OF THE PROJECT

The project aims to develop a comprehensive text mining algorithm for news categorization, encompassing various tasks such as text preprocessing, keyword extraction, topic analysis, and accurate prediction of news article types. The project begins with data collection, acquiring a dataset of news articles along with their respective categories. Subsequently, the text mining pipeline commences with text preprocessing, involving the cleansing of data and standardization of text through techniques like tokenization, stop-word removal, and stemming/lemmatization. Following this, the algorithm extracts keywords or phrases indicative of each article's content using methods like TFIDF. Simultaneously, topic analysis is conducted to discern underlying themes within the news articles, potentially utilizing word similarity measures or advanced embedding techniques. Additionally, machine learning models, such as Multi-layer Perceptron (MLP), are employed to predict the type or category of news articles accurately. These models are trained on labeled data, learning to classify articles into predefined categories based on their textual features. Throughoutthe project, evaluation metrics are utilized to assess the performance of the text-mining algorithm, ensuring its efficacy in real-world scenarios. The project culminates in the deployment of the algorithm, providing users with a powerful tool for efficiently accessingand organizing news content tailored to their preferences and interests. Overall, the project encompasses a comprehensive approach to news categorization, leveraging text mining and machine learning techniques to enhance information retrieval and consumption.

FREQUENCY IDENTIFICATION

In this module, can calculate the term frequency and inverse document frequency. In information retrieval, tf–idf or TFIDF, short for term frequency-inverse document frequency, is a numerical statistic that is intended to reflect how important a word is to a document in a collection or corpus. It is often used as a weighting factor in searches of information retrieval, text mining, and user modeling. The tf-idf value increases proportionally to the number of times a word appears in the document and is offset by thefrequency of the word in the corpus, which helps to adjust for the fact that some words appear more frequently in general. Then calculate the values of entropy and probability of IDF. Entropy gives higher weight to the terms with less frequency in a few documents. Normal is used to correct discrepancies in document lengths and also normalize the document vectors. ProbIDF is similar to IDF and assigns a very low negative weight for the terms occurring in every document.

KEYWORD IDENTIFICATION

Multi-layer perceptron algorithm is used to build the model based on multiple news types. Design the architecture of the MLP model, including the number of layers, the number of neurons in each layer, and the activation functions. Specify the input dimension based on the encoding method used for text data. Choose appropriate activation functions for hidden layers (e.g., ReLU)and output layers (e.g., soft ax for multi-class classification). Specify the loss function, optimizer, and metrics for training the model. For multi-class classification, categorical 7 cross-entropy is commonly used as the loss function. Evaluate the trained model on thetest set to assess its performance using metrics like accuracy, precision, recall, and F1-score.

NEWS CLASSIFICATION

Once satisfied with the model's performance, deploy it in a production environment where it can classify news articles into different categories in real time. This systematic approach ensures the development of a robust MLP-based news classification system capable of accurately categorizing articles across diverse.

BACKGROUND OF THE WORKINSERT DATA

Today internet contains a vast amount of electronic collections that often contain high-quality information. However, usually,the Internet provides more information than is needed. The user wants to select the best collection of data for particular informationneeds in the minimum possible time. Text summarization is one of the applications of information retrieval, which is the methodof condensing the input text into a shorter version, preserving its information content and overall meaning. There has been a hugeamount of work on query-specific summarization of documents using similarity measures. Any standard text file can be uploadedto this module. In this module, can collect a large amount of data in the form of a CSV file and the contents may be any field andany size. Design the interface to admin for analyses of the news content based on domains.

CLASSIFICATION OF TEXTING

In the first step, the text documents are collected which are present in a CSV file. Document Pre- Processing In this process,the given input document is processed for removing redundancies, inconsistencies, separate words, and stemming and documents are prepared for the next step, the stages performed are as follows: Tokenization The given document is considered as a string and identifying single word in document i.e. the given document string is divided into one unit or token. Removal of Stop Word In thisstep the removal of usual words like a, an, but, and, of, the, etc. is done. Stemming A stem is a natural group of words with equal (orvery similar) meaning. This method describes the base of a particular word. Inflectional and derivational stemming are two types ofmethods. One of the popular algorithms for stemming is Porter’s algorithm.

FREQUENCY IDENTIFICATION

In this module, can calculate the term frequency and inverse document frequency. In information retrieval, tf–idf or TFIDF, short for term frequency-inverse document frequency, is a numerical statistic that is intended to reflect how important a word is to a document in a collection or corpus. It is often used as a weighting factor in searches for information retrieval, text mining,and user modeling. The tf-idf value increases proportionally to the number of times a word appears in the document and is offset bythe frequency of the word in the corpus, which helps to adjust for the fact that some words appear more frequently in general. Thencalculate the values of entropy and probability of IDF. Entropy gives higher weight to the terms with less frequency in a few documents. Normal is used to correct discrepancies in document lengths and also normalize the document vectors. ProbIDF is similar to IDF and assigns a very low negative weight for the terms occurring in every document.

KEYWORD IDENTIFICATION

Multi-layer perceptron algorithm is used to build the model based on multiple news types. Design the architecture of the MLP model, including the number of layers, the number of neurons in each layer, and the activation functions. Specify the input dimension based on the encoding method used for text data. Choose appropriate activation functions for hidden layers (e.g., ReLU) and output layers (e.g., softax for multi-class classification). Specify the loss function, optimizer, and metrics for training themodel. For multi-class classification, categorical 7cross-entropy is commonly used as the loss function. Evaluate the trained modelon the test set to assess its performance using metrics like accuracy, precision, recall, and F1- score.

NEWS CLASSIFICATION

Once satisfied with the model's performance, deploy it in a production environment where it can classify news articles into different categories in real time. This systematic approach ensures the development of a robust MLP-based news classification system capable of accurately categorizing articles across diverse.

PROPOSED SYSTEM

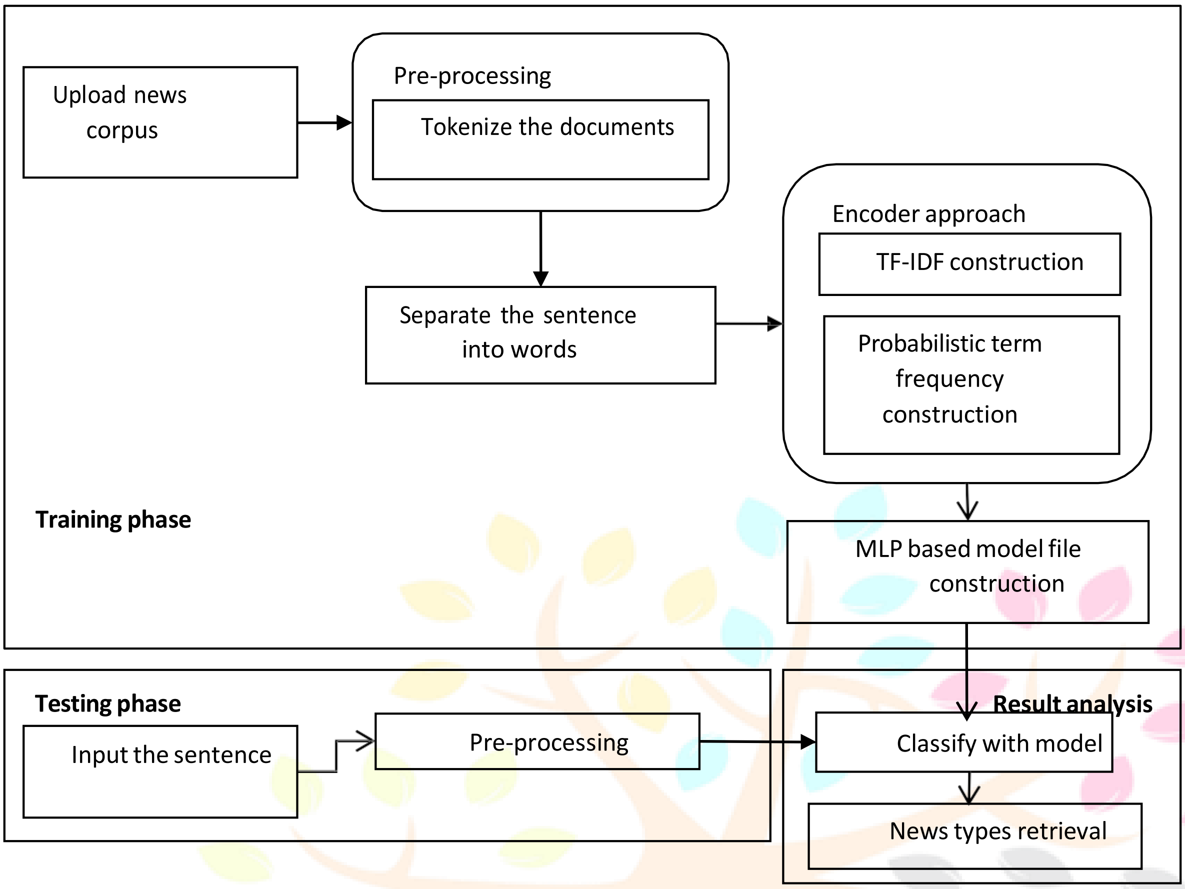
In the proposed system we can implement a text mining algorithm for keyword extraction and topic analysis while predicting the type of news accurately using a deep learning algorithm like Multi-layer Perceptron (MLP), several steps are involved. Initially,the text data undergoes preprocessing, which includes removing HTML tags, special characters, and punctuation. Following this, the text is tokenized into individual words or sub-words, and stop words commonly occurring words are eliminated. Additionally, stemming or lemmatization is applied to reduce words to their base form, aiding in standardization. Subsequently, keyword extraction techniques like TF-IDF are employed to identify significant words or phrases within the text. This involves calculatingimportance scores based on term frequency and inverse document frequency, enabling the extraction of the most relevant keywords.In for topic analysis, the similarity between words can be computed, potentially utilizing methods such as cosine similarity or word embeddings. By identifying words with high similarity scores, topics within the text can be discerned. Furthermore, deep learningalgorithms like MLP can be utilized to predict the type of news accurately. By training the MLP model on labeled data, it learns toclassify news articles into predefined categories based on their textual content. Through this process, the algorithm gains the abilityto generalize and make predictions on unseen data, facilitating efficient and precise news classification. Integrating these techniquesforms a comprehensive text mining pipeline capable of extracting keywords, analyzing topics, and accurately predicting news types, contributing to enhanced understanding and organization of textual data.

- Very effective in constructing relevant feature vectors.
- Characterize the document to overcome the outliers.
- Reduce computational complexity.

SYSTEM ARCHITECTURE

A system architecture or systems architecture is the conceptual model that defines the structure, behavior, and viewsof a system. An architecture description is a formal description and representation of a system, organized in a way that supports reasoning about the structures and behaviors of the system. System architecture can comprise system components, the externally visible properties of those components, and the relationships (e.g. the behavior) between them.

It can provide a plan from which products can be procured, and systems developed, that will work together to implementthe overall system. There have been efforts to formalize languages to describe system architecture; collectively these are called architecture description languages (ADLs).



CONCLUSION

The development of a Multi-layer Perceptron (MLP)-based news classification system presents a powerful solution for efficiently organizing and categorizing news articles. By leveraging MLPs, we can harness the computational power of deep learningto effectively capture complex relationships within textual data, leading to accurate classification results. Through meticulous data preprocessing, model definition, training, and evaluation, we ensure the robustness and reliability of the system. The systematic approach adopted ensures that the model can handle diverse datasets and generalize well to unseen data, Thus enhancing its utilityin real-world applications. Moreover, finetuning and optimization techniques enable us to continually improve the model's performance and adapt it to evolving needs and challenges. Ultimately, the deployment of the MLP-based news classification systemin production environments enables seamless and accurate categorization of news articles, facilitating streamlined access to relevantinformation for users. As information continues to proliferate in the digital landscape, the development and deployment of such advanced classification systems are essential for enhancing.

ACKNOWLEDGMENT

We are grateful to Mr. Ramalingam Sakthivelan., Assistant Professor, CSE Department, Paavai Engineering College (Autonomous) for mentoring us to present this paper successfully.

REFERENCES

[1] Asada, Muhammad Imran, et al. "Classification of News Articles using Supervised Machine Learning Approach." Pakistan Journal of Engineering and Technology 3.03 (2020): 262-3025.

[2] Bajaj, Ashish. "Exposing the Vulnerabilities of Deep Learning Models in News Classification." 20234th International Conference on Innovative Trends in Information Technology (ICITIIT). IEEE,2023.1258-963

[3] Daud, Shahzada, et al. "Topic classification of online news articles using optimized machine learning models." Computers 12.1 (2023): 1678- 3569.

[4] Jiang, Zhiying, et al. "Low-Resource" TextClassification: A Parameter-Free Classification Method with Compressors." Findings of the Association for Computational Linguistics: ACL2023. 2023.

[5] Nikam, Rupali Dalvi. "Machine learning algorithm based model for classification of fake news on twitter." 2020 Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC). IEEE,2020.1247-3 Electron., submitted for publication.

[6] Petukhova, Alina, and Nuno Facade. "MNDS: A multileveled news dataset for news articles hierarchical classification." Data 8.5 (2023): 7425-369.

[7] 2404360_218218_545_552 2404360_218218_545_552Rothera, Dhiren Facade, et al. "A taxonomy of fake news classification techniques: Survey and implementation aspects." IEEE Access 10 (2022): 30367-30394..