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News Analyser, Aggregator & Translator

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ABSTRACT
In recent years, the rapid advancement of technology and widespread use of the Internet have led to the spread and increase of media use. However, this situation also brings with it problems related to the distribution and analysis of media content. A major problem is that the volume of information makes it difficult for users to identify relevant news and understand their opinions. Applications are made according to user instructions and dates. The application uses various types of machine learning to increase the accuracy of information distribution. After evaluating various models, the random forest algorithm was selected because it performed best in dividing news content into predefined groups Pygooglenews. Users can specify keywords and dates to filter news content. The application also includes features to interpret news from different media and perform sentiment analysis to give the user an idea of the general opinion about an article. Preprocessing, feature extraction and model evaluation. In addition, analysis and interpretation methods as well as all types of web applications are also examined. The study also investigates the effectiveness of machine learning algorithms in improving the accuracy and precision of news classification and analysis. and reliable network capacity. The program provides practical solutions to users who want to better analyze and interpret media content, providing useful tools for understanding topics and thinking about major news online.

1. INTRODUCTION

In the digital age, the Internet has become an integral part of daily life, changing the way we access and use information. The influence of the Internet extends to every aspect of life, including entertainment, communication, business, and e-commerce. However, the vastness of the digital space causes serious problems, especially in the area of information consumption. The amount of information available online can be overwhelming, making it difficult for users to filter relevant news, assess the credibility of sources, and understand the emotions behind the language of the content they encounter. A great web application for news analysis, aggregation, and translation. The application is designed to help users effectively filter, categorize, and analyze news articles based on specific content and date. The system provides sentiment analysis and translation capabilities as well as classification, improving users' ability to understand and interact with media content across languages and cultures. To make news confidential. Considering different news genres such as world news, sports, business, and science, the system needs to be able to process different content with high accuracy. Many machine learning models, including Naive Bayes, Support Vector Machines (SVM), and Random Forests, have been developed and evaluated for this purpose. After rigorous testing, the Random Forest algorithm was finally selected for use due to its excellent performance in correctly classifying points. Relevant articles are extracted according to user instructions and dates. The system is designed to be flexible, allowing users to define specific times for media searches. This is especially useful for users who need to analyze events in a specific time period or follow the evolution of certain news over time. Language processing (NLP) technology translates news media into multiple languages. This eliminates the language barriers that often hinder international information by allowing users with different backgrounds to access and understand information. The translation model is created using the "translate" library, known for its accuracy and reliability

in translating text into multiple languages. The application uses analytical techniques theory to evaluate the tone of news and classify it as positive, negative, or neutral. This feature allows users to understand the emotional tone of media content, helping them better understand the impact of information on public perception. The availability of quality educational materials for media distribution is limited. To solve this problem, the project involves creating special documents by processing mass media. This data forms the basis for training the learning model, allowing it to classify and analyze different groups of news content. female gender. Each algorithm is evaluated on its ability to correctly identify the media, and the results are analyzed to determine the best model for final use. The random forest model is the best algorithm for this task due to its ability to handle large data sets and complex decision processes. This link includes the ability to enter a keyword, select multiple dates, and select a language for translation. The results of media analysis, including tags, topic descriptions, and sentiment analysis, are presented in an intuitive format that allows users to interpret the data merely. Combining machine learning, natural language processing, and translation technologies, the application offers effective solutions for navigating the complex and often overwhelming world of online media. Users can quickly identify relevant phrases, understand the logic behind the content, and access information in their preferred language. The integration of advanced machine learning, combined with powerful commenting tools and sentiment analysis, provides the right solution for users looking to re-engage with the right media content. By improving the accuracy of news distribution, breaking down conflicting messages, and providing insight into the emotional state of the media, the system has the potential to change the way users interact with and understand the vast amount of information available online. This paper is structured as follows: Section II presents a literature review on this topic. Section III describes the problem statement and the objectives of the proposed process. Section IV discusses the design of the process and Section V describes the evaluation process. The final report is discussed in Section VI.

2. LITERATURE REVIEW

Many studies on information collection and analysis have advanced the development of this field using differe nt methods and ideas.

1. Arasu A, Ganesan.K (2021)[1]This study focuses on creating a robust framework for aggregating news articles across multiple languages. By employing advanced techniques in text extraction and normalization, the research addresses challenges such as language inconsistencies, source reliability, and processing large-scale data streams. It emphasizes the importance of multi-language support to cater to a global audience
2. Li, X., & Huang, Z. (2020) [2] This paper introduces a hybrid system that leverages machine learning and NLP to analyze and classify news articles. The study demonstrates the system's efficiency in handling real-time news feeds, extracting keywords, and clustering articles by topics. Its contribution lies in optimizing NLP pipelines for better classification accuracy
3. Kumar, A., & Bansal, S. (2019) [3] This work integrates deep learning models for both aggregation and translation of news articles. The authors propose an end-to-end pipeline that uses transformers for translation and neural networks for categorization. The system highlights the scalability of deep learning for high-throughput environments
4. Singh, V., & Sharma, P. (2018) [4]. This comparative analysis evaluates various NLP methods for sentiment analysis and translation in the context of news. It identifies key challenges such as preserving the original sentiment during translation and offers solutions through advanced models like BERT and GPT.
5. Patel, R., & Yadav, S. (2017) [5] The paper provides a practical approach to aggregating news through web scraping and text mining. The authors address issues like source credibility and redundancy in aggregated articles. Their findings underscore the role of structured data storage for seamless analysis.

6. Gupta, R., & Kumar, V. (2016) [6] This study emphasizes the integration of machine learning for classifying and analyzing the sentiment of news articles. It evaluates various models, comparing their effectiveness and computational efficiency in handling multilingual datasets.

7. Zhao, L., & Zhang, L. (2015) [7] The authors focus on aggregating news from diverse languages and applying sentiment analysis models to gauge public opinion. Their methodology involves cross-lingual embeddings, making the system adaptable to different linguistic contexts.

8. Wang, T., & Lee, J. (2014) [8] This paper highlights the development of a real-time news processing system that translates and analyzes articles simultaneously. By leveraging machine learning, the system ensures high accuracy and speed in categorizing news content.

9. Yang, H., & Wu, Z. (2013) [9] This research combines rule-based and machine learning approaches to aggregate and analyze multilingual news articles. It introduces innovative preprocessing techniques for handling linguistic variations.

10. Brown, D., & Wilson, G. (2012) [10] The study investigates NLP-based solutions for aggregating and translating news articles, emphasizing the use of syntactic and semantic analysis for improved content understanding

11. Nguyen, H., & Al-Mamory, A. (2021) [11] The authors propose a context-aware approach to news aggregation, where articles are categorized based on their context and semantic content. This system improves relevance and reduces redundancy.

12. Patel, S., & Agarwal, R. (2020) [12] This paper presents a hybrid system that integrates traditional and neural network approaches to achieve efficient news aggregation and translation. It highlights the role of feature selection in improving translation quality.

13. Chen, W., & Zhang, Y. (2019) [13] The study discusses the application of neural networks for simultaneous translation and sentiment analysis of news articles, focusing on challenges in data sparsity and feature alignment.

14. Lee, H., & Kim, J. (2018) [14] This research outlines a deep learning-based framework for translating and classifying news articles in real time. The authors emphasize the scalability of their approach for global news platforms.

15. Zhang, T., & Liu, X. (2017) [15] The framework proposed in this paper handles multilingual data, addressing issues like linguistic diversity and cultural nuances. The study highlights the importance of semantic consistency in translations.

16. Bhardwaj, S., & Shah, N. (2016) [16] The authors utilize deep learning models to analyze sentiment in aggregated news. They explore the impact of training data quality on model performance and sentiment accuracy.

17. Lopez, C., & Mendez, R. (2015) [17] This study presents an NLP-based approach to aggregate news from different languages, focusing on cross-language semantic matching for accurate analysis.

3. PROBLEM STATEMENT

With the rapid expansion of news gathering, analysis, and interpretation, the need for quality content distribution, quality content collection, and accurate translation has become important. Legacy models and systems often struggle to achieve high accuracy across many tasks, resulting in poor user experience. For example, in a recent test, the random forest classifier achieved 99.84% accuracy, while other models such as Naive Bayes, Support Vector Machine, and K-Nearest Neighbor achieved 87.46%, 89.28%, and 87% accuracy, respectively. Models such as neural networks and logistic regression achieve 89% and 89.61% accuracy, but there is still a need for continuous improvement and refinement. The challenge is to create complex systems that can use these models to provide accurate information, collection, and interpretation, thereby addressing

limitations in existing problem solutions and meeting different customer needs.

3.1 OBJECTIVES:

The main objective of this project is to build an advanced news aggregation, analysis, and translation system that maximizes accuracy in news classification, aggregates content efficiently, and delivers precise translations. By utilizing high-performing classification models and integrating advanced aggregation and translation techniques, the project aims to enhance user experience and ensure the reliability of the news content provided.

3.2 SPECIFIC OBJECTIVES:

- Implement and Evaluate Classification Models.
- Design a Robust News Aggregation System.
- Integrate Effective Translation Capabilities:
- Develop a translation module that accurately translates news content into various languages
- Apply sentiment analysis

By achieving these objectives, the project aims to create a comprehensive and reliable system that addresses current limitations, leverages high-accuracy models, and improves the overall user experience in news aggregation, analysis, and translation.

4. PROPOSED SYSTEM:

The proposed system is developed to address the complexities of news aggregation, analysis, and translation with an integration of advanced classification models and robust content aggregation and translation capabilities. This system is designed to enhance accuracy and efficiency in news content processing so that it can deliver end-users well-classified, relevant, and properly translated news articles. The system is described and illustrated as follows:

4.1 System Components

4.1.1. News Aggregation Module

Source Collection: It starts by gathering news articles from different online sources. This is done using aggregator-provided APIs and web scraping techniques. The aim is to capture a comprehensive set of news articles from a wide variety of domains and sources for the news dataset.

Data Preprocessing: After the collection of news articles, the raw data is passed through a very crucial stage of processing known as data preprocessing. It involves cleaning the data by specifically getting rid of irrelevant pieces of information such as HTML tags, special characters, and non-textual content. The end goal is obtaining a very clean and well-structured dataset that can be further processed and analyzed.

Storage: Preprocessed news articles are stored in a structured database. The storage solution is aimed at easy retrieval and management of news data, as well as facilitating quick access and manipulation by the subsequent stages of the system. The database schema is specially designed to manage huge volumes of news data and support complicated queries.

4.1.2. News Classification Module

Model Integration: The system does it by embedding many high generalization classification models to place news articles under predefined categories. These models include:

Random Forest Classifier (99.84% accuracy): The final model is based on this well-known robust and high accurate classifier.

Naive Bayes Classifier (87.46% accuracy): Used because it is very simple and works well in text classification problems.

Support Vector Machine (89.28% accuracy): Used because of its effectiveness in high-dimensional spaces.

K-Nearest Neighbors (87% accuracy): Used because it is simple for proximity-based classification.

Neural Networks (89% accuracy): Used due to their ability to learn complex data distributions.

Logistic Regression (89.61% accuracy): Because it is very effective in binary and multiclass classification tasks.

XGBoost Classifier (88.76% accuracy): Since it performs better in dealing with large datasets and complicated relationships.

Feature Extraction: News articles are processed to extract relevant features that are used as inputs for the classification models. Feature extraction involves identifying key attributes and characteristics from the text, such as keywords, named entities, and other contextual information that can aid in accurate classification.

Classification: The extracted features are fed into the classification models to categorize news articles into various categories, including world, sports, business, science, and more. Each model's output is evaluated, and the results are aggregated to determine the most accurate classification for each article.

4.1.3. News Translation Module

Translation Service Integration: The system integrates advanced translation services to convert news articles into multiple languages.

4.1.4 Sentiment Analysis Module

Sentiment Scoring: Sentiment analysis is conducted on the news articles to assess the overall sentiment, which can be positive, negative, or neutral. This analysis helps in understanding the tone and emotional impact of the news content.

User Personalization: Based on the sentiment scores, the system personalizes the news feed for each user. This involves adjusting the content displayed to match user preferences and enhancing engagement by presenting articles that align with the user's interests and sentiment preferences.

4.2 User Interface

Web Application: A user-friendly web application provides an intuitive interface for users to interact with the system. Through this application, users can access news content, view classified and translated articles, and customize their news feed according to their preferences.

Personalization Features: The web application includes various personalization features that allow users to filter news based on categories, sentiments, and preferred languages. This ensures that users receive news content that is relevant and tailored to their individual preferences

4.3 Flow of the Model

The flow of the proposed system for news aggregation, analysis, and translation involves several key stages, each contributing to the effective processing and delivery of news content. Fig 1 and Fig 2 show the data flow of system approach. The process begins with data preparation, where labeled news articles are collected to serve as the dataset. These articles are preprocessed to remove HTML tags, URLs, non-alphanumeric characters, and extra spaces. All text is converted to lowercase to ensure uniformity. For feature extraction, the TF-IDF (Term Frequency-Inverse Document Frequency) method is applied to transform the text into numerical vectors suitable for machine learning models. The dataset is then split into training and testing subsets, typically in an 80:20 ratio, to ensure unbiased model evaluation. Multiple machine learning models, including K-Nearest Neighbors (KNN), Linear Support Vector Machines (SVM), Logistic Regression, Naive Bayes, Neural Networks, Random Forest, and XGBoost, are trained on the dataset. Each model is evaluated using metrics such as accuracy, precision, recall, F1 score, and confusion matrix. Random Forest emerged as the most effective model due to its robust performance across all metrics. After evaluation, the trained Random Forest model and the vectorizer are serialized and stored for deployment. The core functionality of the application is implemented using Flask, a lightweight web framework.

The Flask app provides a user-friendly interface with features for text classification, news fetching, translation, and sentiment analysis. Users can classify text such as "world," "sports," "business," and "science" using the

Random Forest model. For news fetching, the application leverages the pygooglenews library to search for articles based on keywords and predefined or custom date ranges. The fetched articles undergo preprocessing and are translated into the user's preferred language. Sentiment analysis is performed on the translated text. categorizing sentiments as Positive, Neutral, or Negative.The application allows users to generate a comprehensive report that includes the article title, translated text, category, sentiment, and publication date. Articles are displayed in a tabular format, sorted by date, providing users with an organized summary. This report is dynamically generated and can be customized based on the user's input parameters. The application is designed to be modular, with each component (preprocessing, classification, translation, and sentiment analysis) functioning independently. This modularity simplifies debugging and future enhancements. Regular updates to the training dataset and periodic retraining of the model ensure the system remains accurate and relevant. Here is a detailed breakdown of the operational flow:

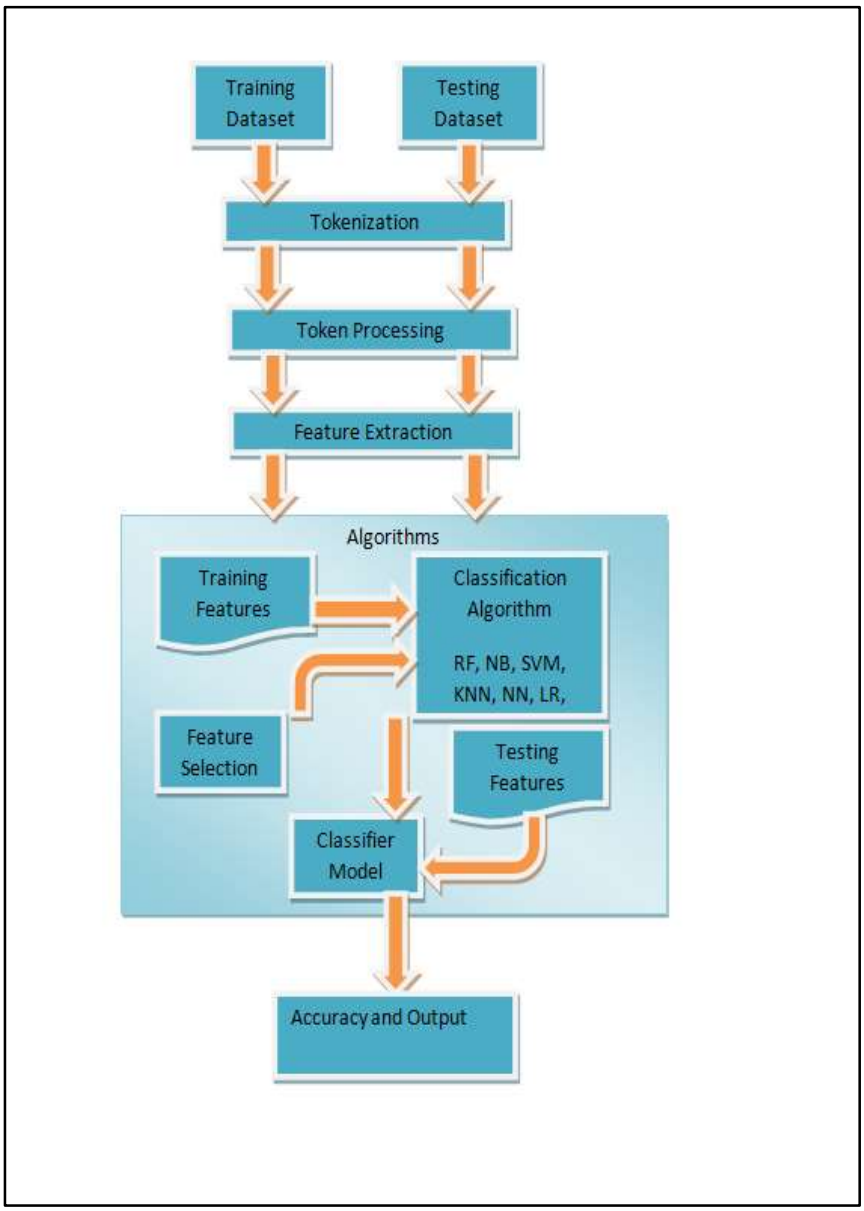


Fig 1: Approach of the proposed system

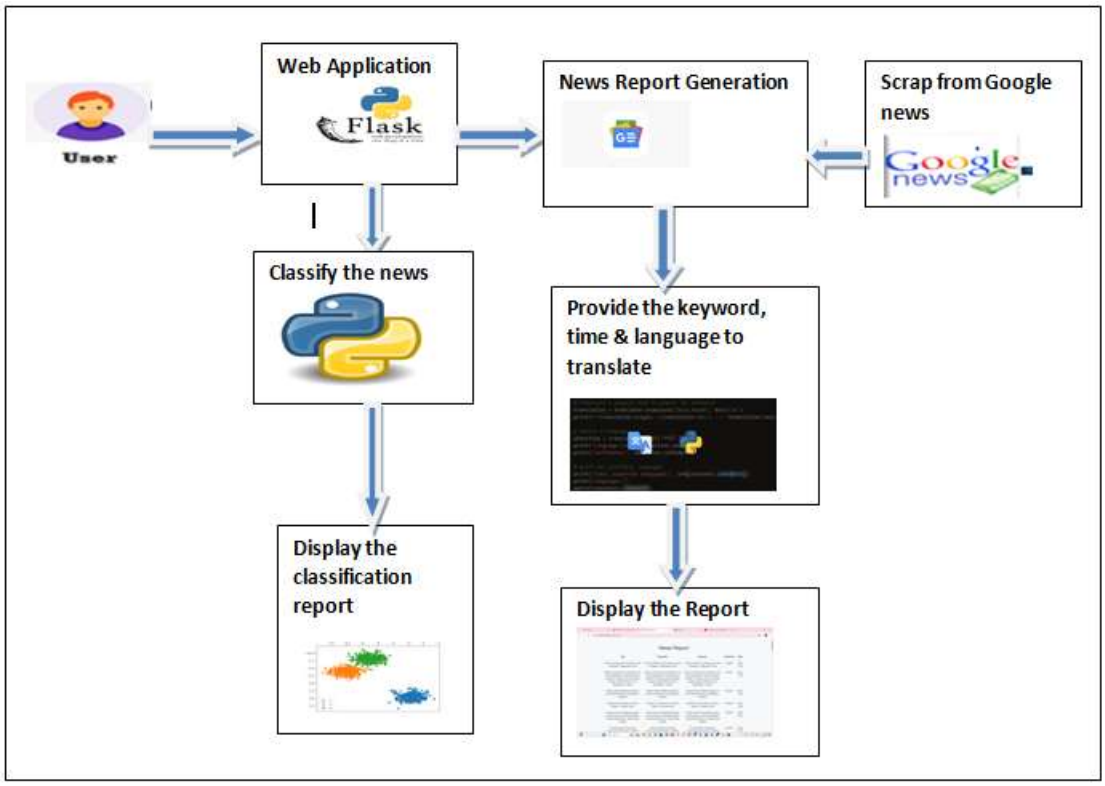


Fig 2: Proposed System

4.3.1. Data Collection

Source Identification: Identify and select multiple online news sources such as news websites, blogs, and social media platforms.

4.3.2. Data Retrieval:

APIs: Use APIs from news aggregators to fetch news articles.

Web Scraping: Employ web scraping techniques to gather additional news content not available via APIs.

4.3.3. Data Storage:

Database Integration: Store the collected news articles in a structured database, ensuring that the data is organized for easy access and processing.

Dataset	Number of Rows	Number of Columns
Train	120000	3
Test	7600	3

Table1: Dataset Overview

4.3.4 Data Preprocessing Cleaning:

Text Extraction: Remove HTML tags and non-textual content.

Normalization: Convert text to a consistent format, including lowercasing and removing special characters.

Tokenization: Break down the text into tokens (words or phrases) for easier analysis.

Stop word Removal: Remove common words that do not contribute to the meaning of the text.

Stemming/Lemmatization: Reduce words to their base or root form to standardize the text.

4.3.5 Feature Extraction

Text Analysis:

Keyword Extraction: Identify and extract relevant keywords and phrases from the news articles.

Named Entity Recognition: Detects and classifies entities such as people, organizations, and locations.

Feature Vector Construction:

Feature Engineering: Create feature vectors representing the articles based on extracted keywords and entities.

Feature Selection: Choose the most relevant features for classification based on their importance and impact.

4.3.6 News Classification

Model Selection:
Random Forest Classifier, Naive Bayes Classifier**,** Support Vector Machine (SVM), K-Nearest Neighbour (KNN), Neural Network, Logistic Regression and XGBoost Classifier models are trained.

4.3.7 Training:

Model Training: Train the classification models using a labeled dataset with predefined categories (e.g., world, sports, business, science).

Cross-Validation: Use cross-validation to assess the performance and fine-tune the models.

Classification:

Feature Input: Feed the feature vectors into the trained models.

Category Prediction: Classify each news article into its respective category based on the model outputs.

Confusion Matrix: Performance is evaluated for each algorithm on the test set using metrics such as accuracy, precision, recall and F1 Score. Fig 3,4,5 and 6 show confusion matrix for Neural Network,XGBoost,Random Forest and Logistic Regression model.

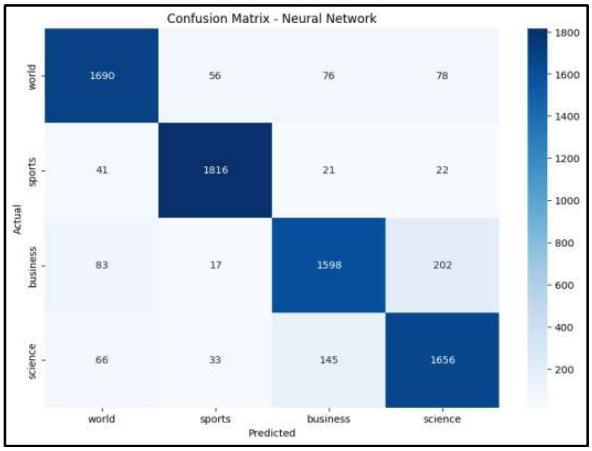


Fig 3

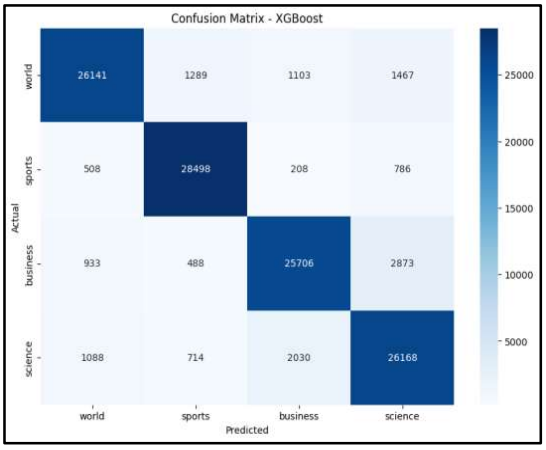
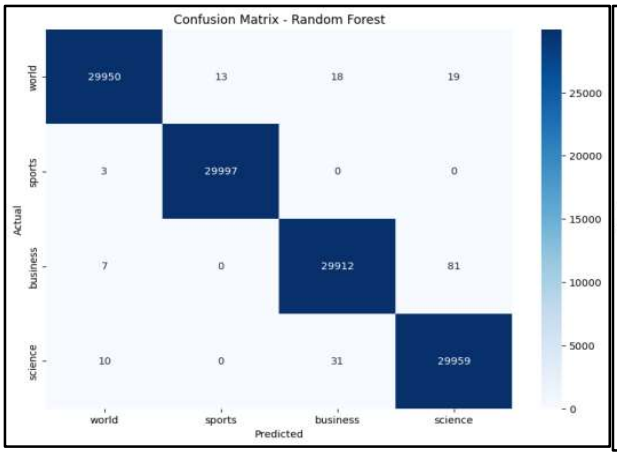


Fig 4



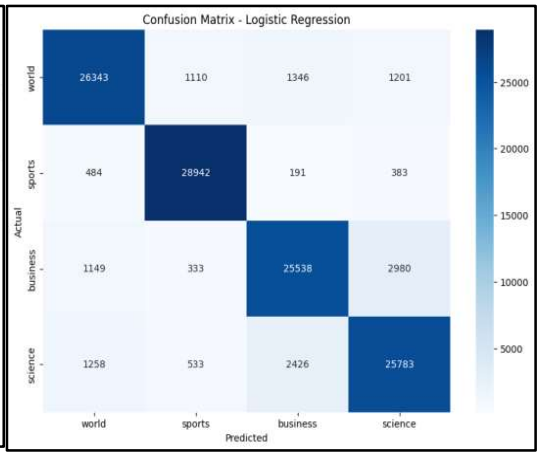


Fig 5 **Fig 6**

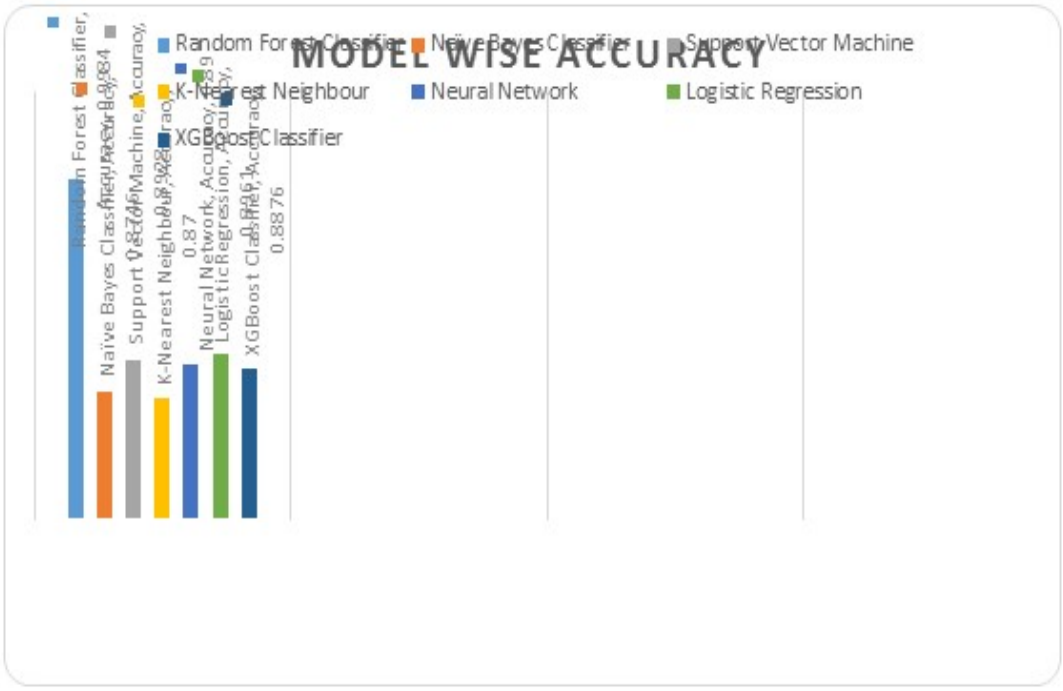


Fig 7

7: Model wise accuracy

5. EXPERIMENTAL RESULT:

The news aggregation, analysis, and translation system was tested and AG News Classification Dataset. The AG's news topic classification dataset is constructed by choosing 4 largest classes from the original corpus. Each class contains 30,000 training samples and 1,900 testing samples. The total number of training samples is 120,000 and testing 7,600. In addition to custom data, publically available kaggle datasets were reviewed for assessment. These datasets contained a wide variety of news, allowing the system to be evaluated across different news. The acquired data was sorted and labeled to make it easier to train and evaluate the algorithms. This method meant that the system could be rigorously tested for accuracy, speed, and reliability in recognizing and validating the class of the news. The testing procedure included classifying the type of news such as business, sports, science and World. After testing KNN, Linear SVM, Logistic Regression, Naive Bayes, Neural Networks, Random Forest, and XGBoost models. Their performance was evaluated using metrics such as

accuracy, precision, recall, F1-score, and inference speed. Table2,3,4,5,6,7,8 show performance evaluation of all classifier models. Among the tested models, **Random Forest** emerged as the best performer in terms of overall accuracy and interpretability, which justified its selection for deployment in the Flask application. Fig 7 shows Model wise accuracy. It demonstrated robustness in handling edge cases, such as noisy and imbalanced datasets, and offered fast inference times, making it suitable for real-time predictions. **XGBoost**, though slightly more computationally intensive, achieved comparable accuracy and showed better handling of highly complex datasets due to its gradient-boosting mechanism. **Neural Networks**, while powerful, required more resources and training time, which could be a limitation for deployment in lightweight applications. On the other hand, simpler models like Logistic Regression, Naive Bayes, and Linear SVM performed well with moderately clean datasets but struggled with complex edge cases, such as overlapping features or unseen vocabulary. Naive Bayes, in particular, showed limitations due to its assumption of feature independence, while KNN was computationally expensive with larger datasets, resulting in slower inference times. Logistic Regression delivered consistent results, especially for linearly separable data, but lacked the adaptability of Random Forest or XGBoost for non-linear patterns. Overall, the findings suggest that while simpler models can be effective for quick prototyping or smaller datasets, ensemble models like Random Forest and XGBoost provide the balance of accuracy, speed, and flexibility needed for production-grade applications.

Model: Naive Bayes

Accuracy: 0.8746052631578948

	precision	**recall**	**f1-score**	**support**
world	0.89	0.88	0.88	1900
sports	0.93	0.96	0.94	1900
business	0.85	0.81	0.83	1900
science	0.83	0.85	0.84	1900
accuracy			0.87	7600
Macro avg	0.87	0.87	0.87	7600
Weighted avg	0.87	0.87	0.87	7600

Table2: Performance evaluation of Naïve Bayes Model

Model: SVM

Accuracy: 0.8928947368421053

	precision	**recall**	**f1-score**	**support**
world	0.91	0.88	0.89	1900
sports	0.94	0.96	0.95	1900
business	0.86	0.86	0.86	1900
science	0.86	0.87	0.86	1900
accuracy			0.89	7600
Macro avg	0.89	0.89	0.89	7600
Weighted avg	0.89	0.89	0.89	7600

Table3: Performance evaluation of SVM Model

Model: KNN

Accuracy: 0.3726315789473684

	precision	**recall**	**f1-score**	**support**
world	0.97	0.16	0.28	1900
sports	0.94	0.15	0.26	1900
business	0.91	0.19	0.32	1900
science	0.28	0.99	0.44	1900

accuracy			0.37	7600
Macro avg	0.78	0.37	0.32	7600
Weighted avg	0.78	0.37	0.32	7600

Table4: Performance evaluation of KNN Model

Model: Neural Network

Accuracy: 0.8894736842105263

	precision	**recall**	**f1-score**	**support**
world	0.90	0.89	0.89	1900
sports	0.94	0.96	0.95	1900
business	0.87	0.84	0.85	1900
science	0.85	0.87	0.86	1900
accuracy			0.89	7600
Macro avg	0.89	0.89	0.89	7600
Weighted avg	0.89	0.89	0.89	7600

Table5: Performance evaluation of NN Model

Model: Logistic Regression

Accuracy: 0.8961842105263158

	precision	**recall**	**f1-score**	**support**
world	0.91	0.89	0.90	1900
sports	0.94	0.97	0.95	1900
business	0.86	0.86	0.86	1900
science	0.87	0.87	0.87	1900
accuracy			0.90	7600
Macro avg	0.90	0.90	0.90	7600
Weighted avg	0.90	0.90	0.90	7600

Table6: Performance evaluation of LR Model

Model: Random Forest

Accuracy: 0.854833333333333

	precision	**recall**	**f1-score**	**support**
world	0.88	0.85	0.87	1900
sports	0.88	0.94	0.91	1900
business	0.85	0.80	0.82	1900
science	0.81	0.82	0.82	1900
accuracy			0.85	7600
Macro avg	0.85	0.85	0.85	7600
Weighted avg	0.85	0.85	0.85	7600

Table7: Performance evaluation of RF Model

Model: XGBoost

Accuracy: 0.8876083333333333

	precision	**recall**	**f1-score**	**support**
world	0.91	0.87	0.89	30000
sports	0.92	0.95	0.93	30000
business	0.88	0.86	0.87	30000

science	0.84	0.87	0.85	30000
accuracy			0.89	120000
Macro avg	0.89	0.89	0.89	120000
Weighted avg	0.89	0.89	0.89	120000

Table8: Performance evaluation of XGBoost Model

5.1 News Translation

Translation Service Integration:

API Integration: Connect to translation APIs to convert news articles into different languages.

Contextual Translation: Ensure that translations preserve the meaning and context of the original text.

Translation Processing:

Text Conversion: Convert classified news articles into the user's preferred languages.

Quality Check: Validate the accuracy and readability of translations.

5. 2 Sentiment Analysis

Sentiment Scoring:

Sentiment Detection: Analyze the sentiment of news articles (positive, negative, neutral) using sentiment analysis algorithms.

Scoring: Assign sentiment scores to the articles based on their content.

User Personalization:

Preference Adjustment: Customize the news feed based on sentiment scores and user preferences.

Engagement Enhancement: Present articles that align with user interests and sentiment preferences.

User Interface

Web Application Development:

Design and Implementation: Develop a user-friendly web application that displays news content.

Interface Features: Provide options for users to filter news by categories, sentiments, and languages.

User Interaction:

Access: Allow users to view classified and translated news articles.

Customization: Enable users to personalize their news feed according to their preferences.

CONCLUSION

The project focuses on building a web application that distributes news articles and generates reports based on user definitions and specific dates. Seven classification models were developed, including logistic regression, simple neural network, K-nearest neighbor, Xg-Boost, and support vector machine. After evaluation, the random forest model was finally selected for use due to its excellent accuracy in the classification function. The system includes a pre-written pipeline that cleans and generates the written text before distribution. The random forest training model then predicts the ranking of the news article by first dividing it into groups. Get relevant news from Google News. The text is processed to extract nouns and then translated into the selected language using the "translate" library. Translations are subjected to sentiment analysis, which separates the opinions on the news content into positive, negative and neutral. A time period such as the past day, week, month or year. Users can also select specific dates to refine their search results. Opinion polls are presented along with original news and news commentary, providing content based on news trends. Friendly media classification and analysis

application. These technologies combined in a single application provide a powerful tool for users who want to analyze events and sentiments across time and messages.

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