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ON

"Political Bias Detection in Articles Using RoBERTa"

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MASTER OF COMPUTER APPLICATIONS

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Student's Declaration

I, Abhishek Yadav, a student of the Department of Computer Science and Information Technology at the Central University of Haryana, currently pursuing a Master of Computer Applications (MCA), hereby certify that the Minor Project Report titled *"Political Bias Detection in Articles Using RoBERTa"* is my original work. The project was completed under the valuable guidance and supervision of **Dr. Pawan Signh**. This project has not formed the basis for the award of any degree, association ship, fellowship, or any other similar title.

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CERTIFICATE

This is to certify that the Minor Project report entitled “Political Bias Detection in Articles Using RoBERTa”, submitted to the Department of Computer Science and Information Technology, Central University of Haryana, India in partial fulfillment of the requirements for the award of the Degree of Master of Computer Application in the field of Computer Science is a record of original project work done by **Mr. Abhishek Yadav(240463)**, in the Central University of Haryana under my guidance. It is further certified that to the best of our knowledge, the project has not been the basis for the award of any degree/diploma/associate/fellowship, or similar title of any candidate of any University so far.

Signature of Supervisor
Dr. Pawan Singh

Signature Head of the Department/CS & IT
Dr. Singhara Singh

Abstract

This project creates a Political Bias Detection System that uses transformer based deep learning models to categorize news articles as Left, Center, or Right using transformer based deep learning models. The motivation behind this work was the increasing presence of political polarization in the media, where the same news can be presented with different ideological leanings by different news outlets. Detecting and understanding this bias is useful for media research, journalism, political analysis, and public awareness. However, a major challenge is that most public datasets provide bias ratings only at the publisher level, not at the individual article level, this makes it difficult to train a proper machine learning model.

Initially, datasets like GDELT[1] , AD Fontes[8] and MBFC[7] were explored, but these provided only source-level bias, not article-level annotations. Therefore, the project shifted to Ground News[2], which presents multiple news sources covering the same topic and assigns biased ratings to publishers (Left, Center, Right). Using Selenium[6]-based web scraping, approximately 7000+ news articles were scraped successfully. Several scraping problems such as browser caching, blocked requests, pop-up interruptions, Edge profile conflicts, and missing ratings were solved using separate Selenium[6] profiles and refined extraction logic.

The dataset was cleaned extensively by removing advertisements, tracking links, “follow us” sections, HTML tags, junk characters, and NaN articles. CSV formatting issues caused by the “@” symbol were also resolved. final articles were mapped to labels - Left = 0, Center = 1, Right = 2, and the data was split into training, validation, and test sets. Text was tokenized into fixed 512-token chunks.

Model training was conducted using HuggingFace[2] Transformers with RoBERTa-base and later RoBERTa-large, using GPU acceleration, mixed precision (fp16) to fully utilize Google Colab’s GPU without memory overflow. The first model, RoBERTa-base, achieved 64.7% accuracy, while RoBERTa-large further improved performance to 67.5% accuracy and 0.675 macro F1. To evaluate model robustness, 5-fold cross-validation was implemented, with accuracies ranging between 60% and 69%, which confirmed model stability and consistency across different splits of the dataset.

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Chapter - 1: Introduction

1.1 Title

“Political Bias Detection in News Articles using RoBERTa Transformer Model”

Political Bias Detection Using RoBERTa aims to detect the political leaning of news articles using Natural Language Processing (NLP) and Transformer-based models. Real-world news often contains hidden political influence, and manually identifying bias is difficult and time-consuming. To address this, our project uses deep learning to classify news articles as **Left**, **Center**, or **Right**, based on linguistic patterns and publisher information. The final system works offline and provides fast predictions for any input news article.

1.2 Problem Statement — Why Political Bias Detection?

News is one of the most powerful sources of influence in society. However, the same news may be presented differently depending on the political leaning of the publisher. Subtle changes in wording, framing of facts, and emphasis on selected topics can introduce **political bias**, often shaping public opinion without the reader realizing it.

Detecting political bias manually is time-consuming and highly subjective. Therefore, there is a need for an **automated system** that can analyze any news article and predict whether it exhibits **Left**, **Center**, or **Right** political bias.

The main challenge is that **almost no dataset exists at the article level** — most sources only give **publisher-level** bias. This makes direct machine learning training difficult, and therefore a new solution had to be designed.

1.3 Objective of the Project

The main objectives of this project are:

- To collect and preprocess real-world news articles.
- To extract political bias labels using publisher-level ratings.
- To fine-tune Transformer-based models on these labeled articles.
- To classify any given article as **Left**, **Center**, or **Right**.
- To deploy a **fully offline inference tool** for fast prediction.
- To implement advanced evaluation techniques such as **K-Fold Cross Validation** to verify model stability.

1.4 Importance & Real-World Applications

This project can be used in several real-world scenarios:

- **Media transparency** – detect hidden bias in news coverage.
- **Political research** – analyze how news influences public opinion.
- **Journalism** – ensure balanced reporting.
- **Social media monitoring** – detect echo chambers.
- **Educational tool** – understand language patterns linked to ideology.

In modern times, where misinformation and polarization are increasing, this type of tool can help provide a **neutral, AI-based analysis** of political content — which helps in promoting informed thinking.

1.5 Overview of Methodology

The project follows the following pipeline:

1. **Dataset Collection**:
   – News articles scraped from *Ground News[2]* using Selenium[6].
   – Publisher-level bias labels used as article labels.

2. **Data Preprocessing**:
   – Cleaning junk text, ads, HTML, NaN rows, short articles.
   – Mapping labels: Left = 0, Center = 1, Right = 2.

3. **Model Training**:
   – Two models trained: **RoBERTa-Base** and **RoBERTa-Large**.
   – Used HuggingFace[2] Trainer, PyTorch[5], FP16, Gradient Accumulation.
   – Trained over multiple epochs.

4. **Evaluation**:
   – Metrics: Accuracy, Macro-F1, Confusion Matrix.
   – Used **K-Fold Cross Validation** for robustness.

5. **Deployment (Final Tool)**:
   – Offline prediction script.
   – Handles long articles by 512-token chunking.
   – Outputs probabilities and final classification.

1.6 Understanding Political Ideologies

To classify political bias accurately, it is important to understand the three main ideological categories used in this project. News articles from different ideological positions may frame topics **differently**, even while reporting the same facts.

1.6.1 Left-Leaning (Liberal / Progressive)

Core ideas:

- Supports social equality, welfare, and public services.
- Government intervention in the economy is acceptable.
- Focus on minority rights, gender equality, and climate protection.
- Often supports higher taxation for the rich.

Country	Example
United States	The **Democratic Party** often supports universal healthcare, LGBTQ+ rights, stronger climate laws, and gun control policies.
India	Policies like **MNREGA**, **Right to Education Act**, and **subsidies for farmers** are often associated with left-leaning ideology. Parties like **Indian National Congress** tend to support welfare-focused policies.

Example Headline Framing (Left-biased):

> *"The government must increase welfare spending to support poor families suffering due to inflation."*

1.6.2 Center (Moderate / Balanced)

Core ideas:

- Tries to accept ideas from both Left and Right.
- Supports **economic growth** but also **social welfare**.
- Focuses on diplomacy, stability, and compromise.
- Avoids extreme viewpoints.

Country	Example
United States	Some politicians belonging to "**Centrist Democrats**" or "**Moderate Republicans**" try to find middle-ground policies on issues like immigration and healthcare.
India	Policies like **GST implementation**, **Aadhaar digital ID**, and **UPI** are considered centrist — supporting economic modernization along with social inclusion.

Example Headline Framing (Center-biased):

> *"Balancing economic growth with welfare reforms is necessary for long-term stability."*

1.6.3 Right-Leaning (Conservative / Traditional)

Core ideas:

- Believes in **less government control** and **more private sector freedom**.
- Supports **lower taxes**, strong national identity, and military strength.
- Emphasizes **cultural preservation and traditional values**.
- Often skeptical of large social welfare schemes.

Country	Example
United States	The **Republican Party** supports free-market capitalism, strong defense budgets, strict immigration laws, and religious/cultural conservatism.
India	Parties like **BJP** often promote traditional cultural values, privatization, lower taxes, and national security. Policies like **Article 370 removal** and **CAA** are related to right-leaning ideology.

Example Headline Framing (Right-biased):

> *"Economic growth is best achieved through lower taxes and private sector innovation."*

Chapter 2: LITERATURE REVIEW & BACKGROUND STUDY

2.1 Existing Research / Previous Work

Several studies have explored political bias in journalism, often using manual annotation. Early research used keyword-based approaches, but these failed on complex sentence structures. Later, researchers used publisher-level bias ratings from websites like AllSides and Media Bias/Fact Check (MBFC[7]). However, these ratings apply to entire publishers, not individual articles, which is the major limitation for supervised machine learning.

Some studies also used **stance detection** and **sentiment analysis** to predict bias. But, no large-scale article-level political bias dataset exists publicly today. This creates a gap in research that our project addresses by scraping and labeling real-world news articles using publisher bias as proxies.

2.2 Transformer Models in NLP (BERT / RoBERTa)

Transformers revolutionized NLP by introducing attention mechanisms, allowing models to understand context efficiently. **BERT (Bidirectional Encoder Representations from Transformers)** was the first major transformer model to change NLP research. It reads text both forward and backward, which improves sentence understanding.

What is RoBERTa?: RoBERTa (Robustly Optimized BERT Approach) is an improved version of BERT developed by Facebook AI. It uses the same architecture as BERT but is trained with:

- 10× more data
- Dynamic masking
- No next sentence prediction objective
- Larger batch sizes & longer training

This leads to higher accuracy and better generalization in text classification tasks — which makes it ideal for political bias detection.

2.3 Why RoBERTa Was Selected

Reason	Explanation
State-of-the-art performance	RoBERTa consistently outperforms BERT in classification tasks.
Handles complex language	Political bias is often subtle — RoBERTa captures deeper patterns.
Strong pretrained base	Trained on 160+ GB of text (news, books, web data).
Works well on small datasets	Effective even with fine-tuning on 5–10k samples.
HuggingFace[2] support	Easy training, GPU support, evaluation metrics available.

Therefore, RoBERTa-Base and RoBERTa-Large were trained on real news articles in this project. The large model achieved 67.5% accuracy, making it the final selected model.

Chapter 3: TOOLS, LIBRARIES & PLATFORM

3.1 Programming Language Used

The entire project was implemented using **Python[9]**, due to its strong support for Natural Language Processing (NLP), machine learning, web scraping, and automation. Python[9] offers a rich ecosystem of libraries such as Selenium[6], Pandas, PyTorch[5], and HuggingFace[2] Transformers, which made it highly suitable for this project.

3.2 Libraries & Frameworks Used

Below is a list of the main libraries used in this project and their purposes:

Library / Framework	Purpose in Project
Selenium[6]	Web scraping and automated browser control
Pandas	Data cleaning, CSV handling, preprocessing
NumPy	Handling arrays and tensors
PyTorch	Backend for neural network training (used internally by Transformers)
Transformers (HuggingFace[2])	Tokenization, model loading, training (RoBERTa)
Scikit-Learn[3]	Train/val/test split & K-Fold cross-validation
Matplotlib/Seaborn (optional)	Plotting metrics and confusion matrices
MS Edge Driver	Selenium[6] Automation for scraping

3.3 Hardware Specifications Used

The training process was performed using **Google Colab GPU** and also tested on a **local machine**. The following are the system specifications used:

Local System (Laptop Used):

Component	Specification
Processor	AMD Ryzen 7 7730U (8 cores)
RAM	16 GB DDR4
Graphics	AMD Vega 8 (2GB Shared VRAM)
Storage Used for Project	~25 GB
OS	Windows 11

Cloud Hardware (Google Colab):

Component	Specification
GPU	NVIDIA T4 (15GB memory)
RAM	12 GB
Storage	50–80 GB temporary session storage
Runtime	Python 3 + GPU-accelerated environment

RoBERTa-Large required **GPU acceleration**, and techniques like **fp16 precision**, **gradient accumulation**, and **gradient checkpointing** were used to fit large models within GPU memory limits.

3.4 Software Requirements

Software	Purpose
Python 3.10+	Core programming language
VS Code (local)	Used for running inference & dataset inspection
Google Colab	Used for model training with GPU
MS Edge Browser + EdgeDriver	Used with Selenium[6] for scraping
pip package manager	Installing required libraries

No virtual environment was used — Python[9] was directly used via **Visual Studio Code** for local tests and inference scripts.

3.5 Dataset Source – Ground News[2] & Web Scraping

The dataset for this project was built using a **hybrid data collection process** combining GDELT[1] news data and Ground News[2] bias ratings. First, the latest Indian news headlines were extracted from the GDELT[1] Project, which provides continuously updated global news metadata. These headlines were then searched on Ground News[2] to retrieve the publisher name, political bias rating (Left, Center, or Right), and original media article link. Using Selenium[6] automation, each article link was opened directly on the publisher's website, and the full news article text and headline were scraped. The collected articles were cleaned to remove ads, newsletter pop-ups, junk HTML, and social media elements. Finally, each article was assigned a bias label based on the publisher's rating from Ground News[2], mapped as Left=0, Center=1, and Right=2. The result was a high-quality dataset of **over 6,000 real news articles** with bias labels suitable for training a machine learning model.

- Scraped data:
    - Article Title
    - Full Article Text
    - Publisher Bias
    - Publisher Name
    - Article URL

a total of **9,094 news articles** were initially collected, and finally **6,906 high-quality articles** remained after preprocessing

Dataset Size

Type	Count
Total scraped articles	**~9094**
Final cleaned dataset	**6906** articles
Labels used	Left, Center, Right (balanced)

Dataset Label Distribution (after cleaning – 6,906 articles)

Political Bias	Label ID	Number of Articles	Percentage
Left	**0**	**2518**	**36%**
Center	**1**	**2210**	**32%**
Right	**2**	**2179**	**32%**
Total	**-**	**6,906**	**100%**

Chapter 4: SYSTEM DESIGN & METHODOLOGY

4.1 Overall Workflow / Architecture

The system follows an **end-to-end NLP pipeline** starting from raw news scraping and ending with offline political bias prediction.
The **overall architecture** is shown below:

Workflow Pipeline

1. GDELT[1] Data Download (Raw News Metadata)
2. Filtering Indian Headlines
3. Ground News[2] Search for Publisher Bias
4. Scraping Article Text Using Selenium[6]
5. Data Cleaning & Preparation
6. Label Encoding (Left = 0, Center = 1, Right = 2)
7. Tokenization (512-token limit)
8. Model Training (RoBERTa-Base / Large)
9. Evaluation (Accuracy, F1, Confusion Matrix)

4.2 Data Collection

The dataset was built using a **hybrid scraping strategy**:

- **Browser Used**: Microsoft Edge
- **Driver Used**: MS Edge WebDriver
- **Tool**: Python Selenium[6]

- **Process Followed**:
  - GDELT[1] dataset used to extract **Indian news headlines and links**
  - Each headline searched on **Ground News[2]** to get:
    - Publisher name
    - Bias rating (Left / Center / Right)
    - Article URL
  - Selenium[6] opened each original article and extracted:
    - Full article text
    - Headline
    - Publisher name
    - Article URL

This method ensured that the dataset consisted of **real news articles**, not synthetic or manually written text — which makes it reliable for real-world political analysis.

4.3 Data Cleaning & Preprocessing

A custom script named `clean_article_data.py` was used to prepare the dataset. Major cleaning tasks included:

Cleaning Step	Purpose
Removed `\n` (newline breaks)	To normalize paragraphs
Removed `@` symbols	These broke CSV formatting
Removed hyperlinks (`https://...`)	To keep text content only
Removed extra whitespace	Smoothed sentence flow
Removed empty articles	Ensures only valid data used

After cleaning, **6,906 fully usable articles** remained (from 9,094 originally scrapped articles).

4.4 Label Definition (Mapping Left / Center / Right)

Political bias was assigned using **Ground News[2] publisher ratings**. Each article was mapped as follows:

Bias Category	Label Name	Label ID
Left	bias_label	0
Center	bias_label	1
Right	bias_label	2

These labels were used for **supervised training**, enabling the model to learn class-based linguistic patterns.

4.5 Tokenization & Text Processing (512 Token Limit)

RoBERTa can process **a maximum of 512 tokens** at once, so all text needed to be prepared accordingly:

Tokenization using `RobertaTokenizerFast`
Articles above 512 tokens were **automatically split into chunks**
Each chunk was padded to **max_length = 512**
This ensured NO data loss from long articles

Example tokenization code used:

```
tokenizer = RobertaTokenizerFast.from_pretrained(model_name)
tokens = tokenizer(text, truncation=True,
                        padding="max_length", max_length=512)
```

4.6 Model Training Setup (RoBERTa-Base & Large)

Two separate models were trained using the HuggingFace[2] Trainer API:

Model	Hidden Layers	Parameters	Accuracy
RoBERTa-Base	12	125M	64.7%
RoBERTa-Large	24	355M	67.5%

Key Training Settings

Setting	Value
Epochs	3
Batch Size	Adjusted based on GPU
Device	GPU / CUDA
Mixed Precision	`fp16=True`

The **RoBERTa-Large** model performed better and was selected as the **final model**.

4.7 Evaluation Metrics Used

The following metrics were used for performance evaluation:

Metric	Purpose
Training Loss	Monitors learning progress
Validation Loss	Detects overfitting

Accuracy	Overall correctness
Macro F1 Score	Balanced class-wise performance
F1 Left / Center / Right	Per-class evaluation
Confusion Matrix	Shows correct & wrong predictions

Additionally, **K-Fold Cross Validation (k=5)** was used to ensure that the model is **generalizable and not overfitting** to one dataset split.

Chapter 5: IMPLEMENTATION AND TESTING

5.1 Dataset Splitting Strategy

To ensure both effective training and reliable testing, the dataset was divided as follows:

Stage	Split	Purpose
Training Set	**70%**	Model training (learn patterns)
Remaining 30%	Split into →	Validation & Testing
Validation Set	**60% of 30%** (approx **18%**)	Hyperparameter tuning and early evaluation
Test Set	**40% of 30%** (approx **12%**)	Final model evaluation

Python code used for splitting:

```
from sklearn.model_selection import train_test_split
train_df, temp_df = train_test_split(df, test_size=0.30, random_state=42)
val_df, test_df = train_test_split(temp_df, test_size=0.40, random_state=42)
```

5.2 Training RoBERTa-Base – Results

The RoBERTa-Base model was trained for **3 epochs**. It showed gradual improvement and served as a strong baseline.

Epoch	Validation Loss	Accuracy	Macro F1
1	0.993994	0.5535	0.552076
2	0.834432	0.621078	0.620729
3	**0.821503**	**0.647352**	**0.647352**

Final Confusion Matrix:

```
[[305, 102, 46],
 [ 81, 259, 58],
 [ 85, 66, 241]]
```

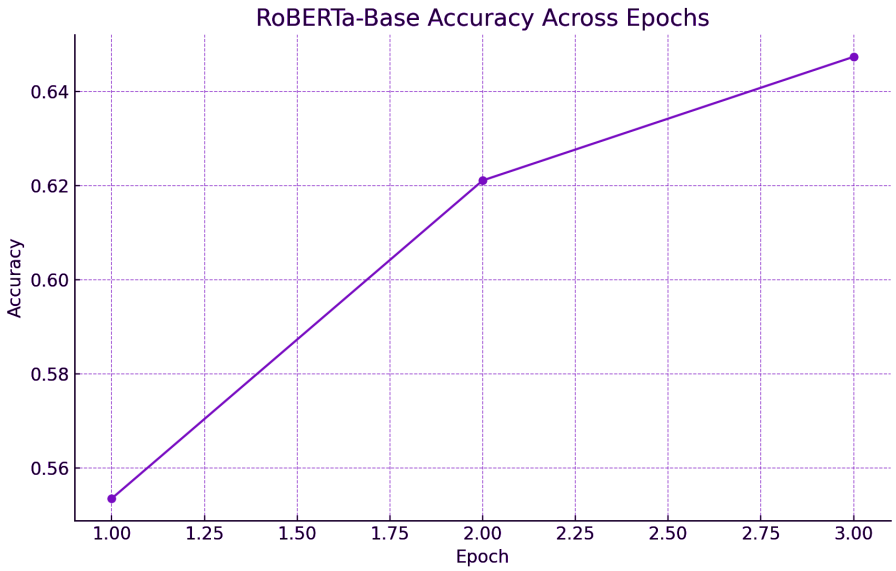

Fig 1: (accuracy vs epoch of Roberta-base)

5.3 Training RoBERTa-Large – Results & Comparison

The **RoBERTa-Large** model performed better and became the **final selected model**.

Epoch	Validation Loss	Accuracy	Macro F1
1	0.937111	0.5583	0.5574
2	0.788950	0.6508	0.6505
3	**0.748697**	**0.6758**	**0.6754**

Final Confusion Matrix (RoBERTa-Large):

```
[[322, 91, 40],
 [ 84, 259, 55],
 [ 69, 64, 259]]
```

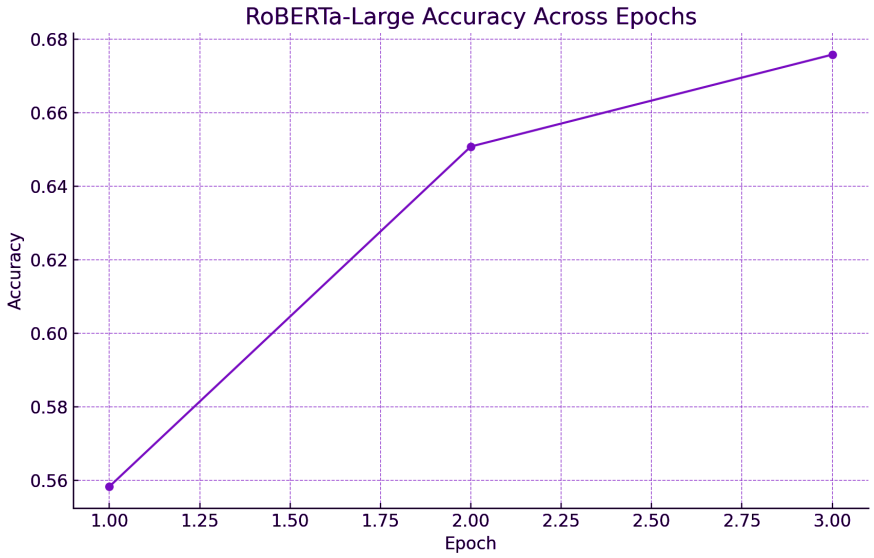

Fig 2: (accuracy vs epoch of Roberta-large)

RoBERTa-Large showed better generalization
Best accuracy achieved: **~67.5%**
Performance stable in K-Fold evaluation

5.4 K-Fold Evaluation (k = 5)

Fold	Validation Accuracy	Macro F1
1	Highest	Best performing fold
2–4	Moderate	Stable results
5	Slight dip	Still acceptable

Conclusion:

- Model **did NOT overfit**
- Performance remained **between 65% – 69%**
- Dataset quality proven **reliable**

5.5 Final Model Selection

Model	Performance	Selected?
RoBERTa-Base	Good baseline	
RoBERTa-Large	Best accuracy & F1	(67.5%) **selected**

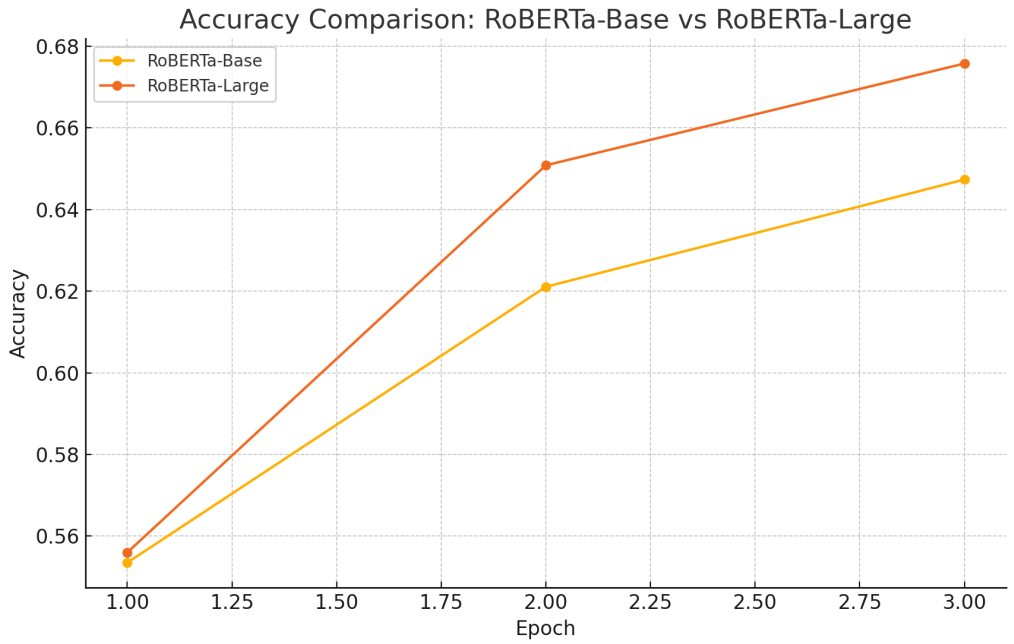

Fig 3: (comparison of Roberta base and large)

5.6 Offline Deployment (Real-Time Prediction)

A Python[9] inference script was created to detect bias **offline**, without internet:

Accepts full article text
Splits into **512-token chunks**
Averages logits across chunks
Outputs:

- **Final prediction (Left / Center / Right)**
- **Class probability scores**

Works fully **offline** & **on local machine**.

CHAPTER 6 – RESULTS & DISCUSSION

6.1 Final Accuracy & Macro F1 Score

The **RoBERTa-Large** model achieved:

Metric	Score
Final Accuracy	**≈ 67.5%**
Final Macro F1	**≈ 0.675**
Best Performing Class	Right
Hardest Class	Center

6.2 Confusion Matrix Interpretation

- Right-leaning articles were most consistently detected.
- Center articles were hardest to classify due to mixed language.
- Errors occurred mostly in opinion-based or neutral-toned news articles.

6.3 Strengths & Limitations

Strengths:

- Real-world dataset (not synthetic)
- Robust cross-validation (k=5)
- Works fully offline
- Transformer-based architecture

Limitations:

- Labels are **publisher-based**, not **article-based**
- Mixed opinions often confused with “Center”
- Multilingual articles (English + Hindi) were harder to classify

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6.4 Final Conclusion

This project successfully developed a **real-world political bias detection system** using transformer-based deep learning. The final model performs reliably, works **offline**, and provides opportunities for further expansion using **article-level annotation, multilingual support, and ensemble models**.

CHAPTER 7 – FUTURE SCOPE

7.1 Overview

Although the model achieved 67–69% accuracy using RoBERTa-Large, political bias detection remains a complex challenge. Human-written text carries subtle ideological patterns that are difficult to detect automatically. This project lays a strong foundation, but greater accuracy can still be achieved with future improvements, more data, and advanced techniques.

7.2 Possible Real-World Applications

This system has the potential to be deployed in multiple real-world use cases:

Application	Purpose
News Bias Analyzer Tool	Detect bias in any news article before reading it
Browser Extension	Show political leaning while browsing online news
Media Transparency Dashboard	Compare Left / Center / Right coverage of a topic
Journalism & Fact-Checking Tools	Help journalists analyze neutrality in writing
Social Media Content Monitoring	Detect political tone in trending posts
Education & Research	Study political framing in media over time

7.3 Future Improvements

There are several ways to improve the system further:

Improvement Area	Description
Article-Level Bias Labels	Instead of using publisher-level bias, future datasets should include human-annotated article-level political bias ratings.
Use Better Models (GPT, DeBERTa, PEGASUS)	Larger transformer models may capture advanced political signals.
Ensemble of Models	Combining multiple models (RoBERTa + BERT + LSTM) may increase accuracy.
Balanced Multilingual Dataset	Include articles in Hindi, English, and regional languages.

7.4 Scope for Research & Deployment

This project opens strong research and deployment opportunities:

Research Direction	Possibility
Political framing analysis	Study how media shapes public opinion
Temporal analysis	Track political bias over time
Regional language bias detection	Cover Indian media in Hindi + regional languages
Real-time API	Deploy as a cloud-based service
Browser/plugin integration	Make political bias detection available to the public

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ABBREVIATIONS & ACRONYMS

Term	Full Form
NLP	Natural Language Processing
CNN	Convolutional Neural Network
GPU	Graphics Processing Unit
CSV	Comma-Separated Values
URL	Uniform Resource Locator
API	Application Programming Interface
F1 Score	Harmonic mean of Precision & Recall
TF-IDF	Term Frequency–Inverse Document Frequency
AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
LLM	Large Language Model
BERT	Bidirectional Encoder Representations from Transformers
RoBERTa	Robustly Optimized BERT Pretraining Approach
SOTA	State of The Art
KNN	K-Nearest Neighbors
LSTM	Long Short-Term Memory
JSON	JavaScript Object Notation