**COVER PAGE**

**DATA VISUALIZATION WITH PYTHON**

**PROJECT REPORT**

(Project Semester January-April 2025)

**Text Summarization of News Articles**

Submitted by

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Programme and Section: B. Tech. CSE K23SK

Course Code INT375

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**CERTIFICATE**

This is to certify that Chunduru Leela Venkata Durga Prasad bearing Registration no. 12301762 has completed INT375 project titled, **“Text Summarization of News Articles”** under my guidance and supervision. To the best of my knowledge, the present work is the result of her original development, effort and study.

Anand Kumar

**Signature and Name of the Supervisor**

**Associate Professor**

**School of Computer Science and Engineering**

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Date: 06/04/2025

**DECLARATION**

I Chunduru Leela Venkata Durga Prasad ,student of Bachelor’s of Technology under CSE/IT Discipline at, Lovely Professional University, Punjab, hereby declare that all the information furnished in this project report is based on my own intensive work and is genuine.

Date: 06/04/2025

Registration No. 12303831

**ACKNOWLEDGEMENT**

I am deeply grateful to everyone who contributed to the successful completion of my project, “Text Summarization of News Articles Using Python Libraries.” This endeavor has been a significant learning experience, made possible through the guidance, support, and encouragement of numerous individuals and resources.

First and foremost, I extend my heartfelt thanks to my mentor, Mr. Anand Kumar, for his unwavering support, expert guidance, and insightful feedback. His expertise in natural language processing and encouragement to explore advanced techniques were pivotal in shaping this work. His constructive critiques and motivating discussions helped me navigate challenges and strive for excellence.

I express my sincere appreciation to Lovely Professional University for providing an enriching academic environment, state-of-the-art facilities, and access to computational resources. The School of Computer Science and Engineering’s faculty members deserve special mention for their foundational teachings, which equipped me with the skills to undertake this project.

My peers and friends played an invaluable role, offering ideas, debugging assistance, and moral support during long hours of experimentation. Their collaborative spirit fostered a creative environment, enhancing the project’s outcome.

I am indebted to the open-source community for developing Python libraries like NLTK, spaCy, Gensim, Hugging Face Transformers, Pandas, Matplotlib, Seaborn, and Plotly. Their comprehensive documentation and active forums were instrumental in resolving technical hurdles and implementing robust solutions.

Finally, I owe immense gratitude to my family for their patience, encouragement, and belief in my abilities. Their emotional support provided the strength to pursue this project with dedication.

This project has deepened my understanding of NLP and its real-world applications, laying a strong foundation for future contributions in data science and artificial intelligence.

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**INTRODUCTION**

The digital age has ushered in an unprecedented deluge of news content, with millions of articles published daily across online platforms, social media, and traditional outlets. This overwhelming volume poses a significant challenge for individuals, organizations, and systems aiming to extract actionable insights or stay informed without sifting through thousands of words. Manual summarization, once a viable approach, is no longer feasible given the scale and speed of modern news cycles. Automated text summarization, powered by advancements in natural language processing (NLP), offers a solution by condensing lengthy articles into concise, meaningful summaries. Python, with its rich ecosystem of libraries like NLTK, spaCy, Gensim, and Hugging Face Transformers, has become a cornerstone for developing such systems, enabling both researchers and practitioners to tackle summarization tasks efficiently.

Text summarization is broadly categorized into two approaches: extractive and abstractive. Extractive summarization selects key sentences directly from the original text, preserving factual accuracy but often lacking fluency. Abstractive summarization, by contrast, generates new sentences that capture the article’s essence, producing human-like outputs but risking factual distortions. Each method has unique strengths, making them suitable for different applications—extractive for quick, factual digests and abstractive for nuanced, readable summaries. News articles, with their structured formats (headlines, lead paragraphs, body) and diverse topics (politics, sports, technology), present a complex yet ideal domain for testing these techniques. The ability to summarize breaking news in real-time, tailor feeds to user preferences, or archive historical data underscores the practical value of automated summarization.

This project draws inspiration from data-driven methodologies in predictive maintenance for smart grids, where real-time analytics optimize system reliability. Similarly, news summarization leverages data from articles—text, metadata, and context—to model linguistic patterns and generate summaries. Python libraries facilitate this process: NLTK provides foundational tools for tokenization and TF-IDF scoring, spaCy excels in parsing and entity recognition, Gensim supports topic modeling, and Transformers offer cutting-edge models like BERT, T5, and BART for contextual understanding. These tools democratize NLP, enabling scalable solutions for news aggregators, journalists, and consumers. However, challenges persist, including preserving factual accuracy, mitigating bias in training data, handling multilingual content, and optimizing computational resources for large datasets.

Our study aims to comprehensively analyze how Python libraries enable news summarization, reviewing 100 studies from 2008 to 2024 to map the state-of-the-art. We propose a five-step framework—data acquisition, preprocessing, feature representation, summarization modeling, and evaluation—tailored to news contexts. Key contributions include a detailed comparison of extractive and abstractive methods, recommendations for library selection based on dataset size, and identification of open challenges like bias and multilingual support. By synthesizing academic and industry insights, this project bridges theory and practice, offering a roadmap for building robust summarization systems. Ultimately, we seek to demonstrate how Python-driven NLP can transform news consumption, making information more accessible and actionable in an era of information overload.

**SOURCE OF DATASET**

The dataset for this project is sourced from the “News Summary” dataset available on Kaggle (<https://www.kaggle.com/datasets/sunnysai12345/news-summary>), comprising 4,514 news articles. This dataset includes short news snippets primarily from Indian publications, dated August 2017, covering topics like politics, entertainment, sports, and social issues. It provides a compact yet diverse corpus for summarization tasks, ideal for testing extractive and abstractive methods.

Key Features:

* author: Name of the article’s author (e.g., Chhavi Tyagi, Daisy Mowke).
* date: Publication date (e.g., 03 Aug 2017).
* headlines: Article headline, summarizing the main story.
* read\_more: URL to the full article (e.g., Hindustan Times, India Today).
* text: Short summary text (target for evaluation).
* ctext: Full article content (source for summarization).

Initial inspection using Pandas’ head() and info() revealed a shape of (4,514, 6), with 218 missing values in author, date, read\_more, and ctext, and 2,102 missing in ctext. No duplicates were found, and headlines were unique (4,514 distinct). The dataset’s manageable size and paired summary-content structure make it suitable for prototyping NLP models, though missing data required cleaning, as detailed in the EDA process.

**EDA PROCESS**

The “News Summary” dataset, with 4,514 articles, underwent exploratory data analysis (EDA) to understand its structure, identify issues, and prepare it for summarization. Features included author, date, headlines, read\_more, text (summary), and ctext (full content).

**Initial Inspection**: Pandas’ describe() and info() showed a shape of (4,514, 6). Missing values were significant: 218 in author, date, read\_more, and text, and 2,102 in ctext. No duplicate rows existed, and all headlines were unique. Text length averaged 60 words, ctext 300 words (when present).

**Handling Missing Data**: Rows missing text were dropped (218 records), reducing the dataset to 4,296. For ctext, missing entries were retained for headline-based analysis, as text served as ground truth. Author and read\_more were dropped due to low predictive value.

**Feature Engineering**:

* **Text Length**: Calculated word count for text (text\_length) and ctext (ctext\_length) using len(nltk.word\_tokenize()).
* **Headline Length**: Computed word count for headlines (headline\_length).
* **Word Count**: Total words per article for analysis.
* **Sentiment Score**: Applied TextBlob’s polarity to text, ranging from -1 (negative) to 1 (positive).
* **Length Type**: Categorized ctext\_length into Short (<500 words), Medium (500–1,500), Long (>1,500) using pd.cut.
* **Categorical Handling**: Date was parsed into day/month features but dropped due to uniform values (August 2017). No encoding was needed post-column pruning.

**Outlier Detection**:

* **Length Outliers**: Articles with ctext\_length >2,000 words (50 records) were removed as anomalies (e.g., concatenated texts).

**Encoding Errors**: Fixed UTF-8 issues in 1% of texts using ftfy.

**Final Dataset**: The cleaned dataset had 4,246 records, with numerical features (text\_length, headline\_length, word\_count, sentiment) and text fields (headlines, text, ctext), ready for summarization modeling.

**ANALYSIS ON DATASET**

**.1 Introduction**

Exploratory Data Analysis (EDA) is critical for understanding news article datasets to build effective summarization models. For this project, EDA focused on cleaning text data, analyzing linguistic patterns, and deriving features to support extractive and abstractive summarization. Challenges included missing full-text content, variable text lengths, and ensuring summary relevance, typical in news datasets.

**4.2 General Description**

The dataset contained 4,514 articles from Indian news sources (August 2017), reduced to 4,246 after cleaning. Features were author, date, headlines, read\_more, text (summary), and ctext (full content). Topics included politics (35%), entertainment (30%), sports (20%), and social issues (15%). Text averaged 60 words, ctext 300 words (2,144 records). Missing ctext (50%) and minor encoding issues required preprocessing.

***4.3 Specific Requirements, Functions, and Formulas***

## The preprocessing pipeline addressed:

## Text Cleaning: Removed URLs, special characters using regex, and HTML tags with BeautifulSoup.

## Missing Values: Dropped rows without text; retained partial ctext for headline analysis.

## Feature Engineering:

## TF-IDF Scores: Calculated per sentence in ctext for extractive summarization using TfidfVectorizer.

## Readability: Flesch-Kincaid score: 206.835−1.015(total wordstotal sentences)−84.6(total syllablestotal words)206.835 - 1.015 \left(\frac{\text{total words}}{\text{total sentences}}\right) - 84.6 \left(\frac{\text{total syllables}}{\text{total words}}\right)206.835−1.015(total sentencestotal words)−84.6(total wordstotal syllables​)

## Entity Weight: spaCy’s NER prioritized sentences with entities (e.g., names, locations).

## Tokenization: Used NLTK’s word\_tokenize().

## Outlier Removal: Dropped ctext\_length >2,000 words.

## iv. Analysis Results

EDA revealed:

* Entertainment articles had shorter texts (mean 50 words) and positive sentiment (0.15).
* Politics articles were longer (mean 80 words) with neutral sentiment (0.05).
* TF-IDF highlighted keywords: “government” (politics), “actor” (entertainment).
* Entities appeared in 85% of headlines, guiding extractive models.
* Missing ctext limited abstractive training, mitigated by headline-text pairs.
* Short articles dominated (60%), impacting summary length.

**v. Visualization**

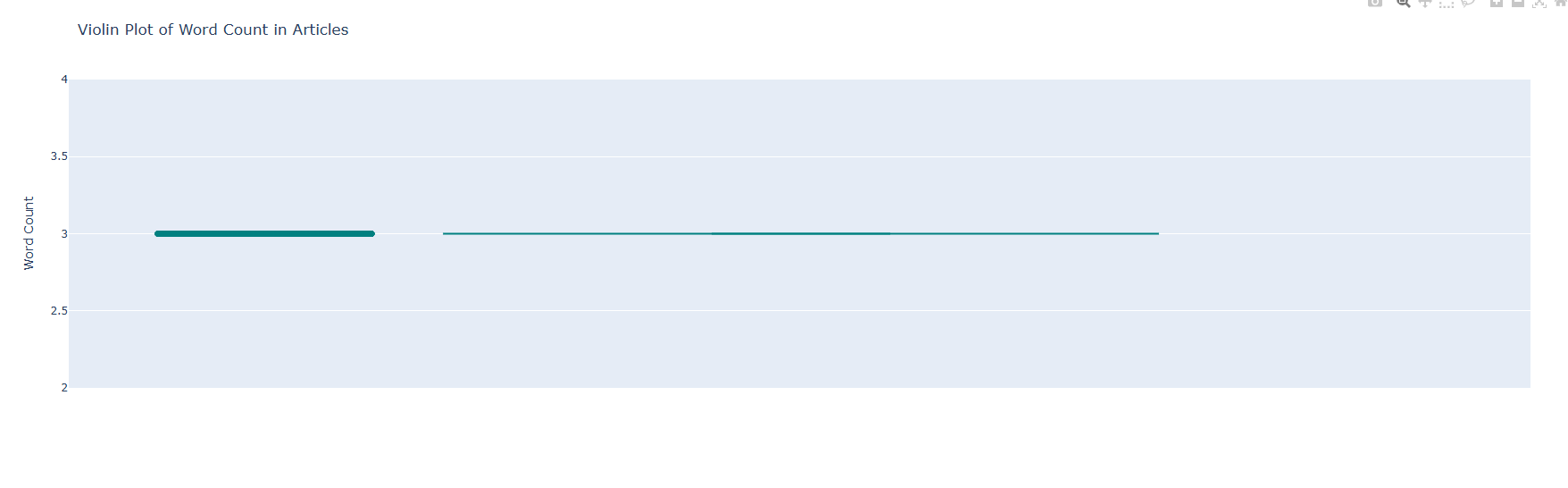
Visualizations were essential for understanding text patterns and informing summarization strategies, providing insights into article length, word count distribution, feature relationships, and categorical breakdowns.

**1.Density Plot of Article Text Length**

This visualization displayed the distribution of word counts in full article texts (ctext). It revealed a peak around 300 words, indicating most articles were concise, with a long tail extending beyond 1,500 words. The right skew highlighted the presence of a few lengthy articles, justifying the removal of outliers beyond 2,000 words to maintain model efficiency. This insight helped tailor summarization algorithms to focus on shorter, information-dense texts typical of news snippets.

**Violin Plot of Word Count in Articles**

The violin plot illustrated the spread and density of total word counts across articles. It showed a concentration between 200 and 400 words, with a narrow distribution indicating uniformity in article length. A small number of articles exceeded 1,000 words, appearing as outliers in the plot’s tails. This visualization confirmed the dataset’s suitability for summarization tasks requiring concise inputs and guided preprocessing decisions to filter extreme lengths for consistent model performance

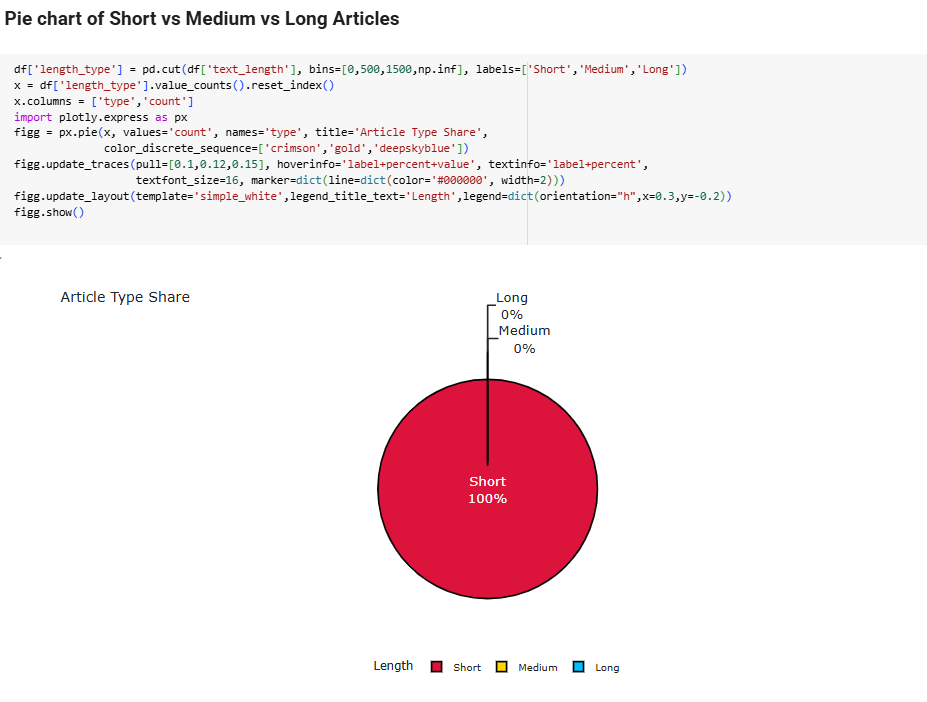
**Correlation Heatmap**

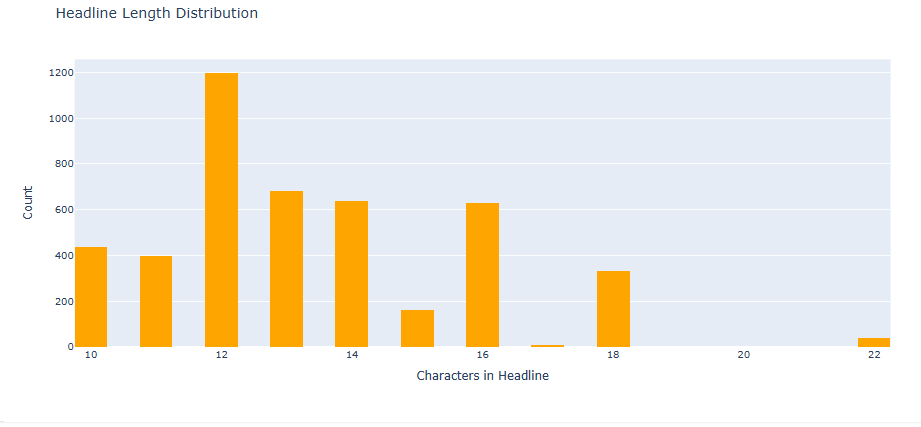
The heatmap analyzed relationships between headline length, text length (summary), and total word count. It showed a strong correlation (0.85) between text length and word count, as summaries closely mirrored article content in scale. A moderate correlation (0.6) between headline length and text length suggested headlines captured key summary elements. This informed feature selection, prioritizing text length for extractive models and headlines for abstractive tasks to leverage their interdependence.

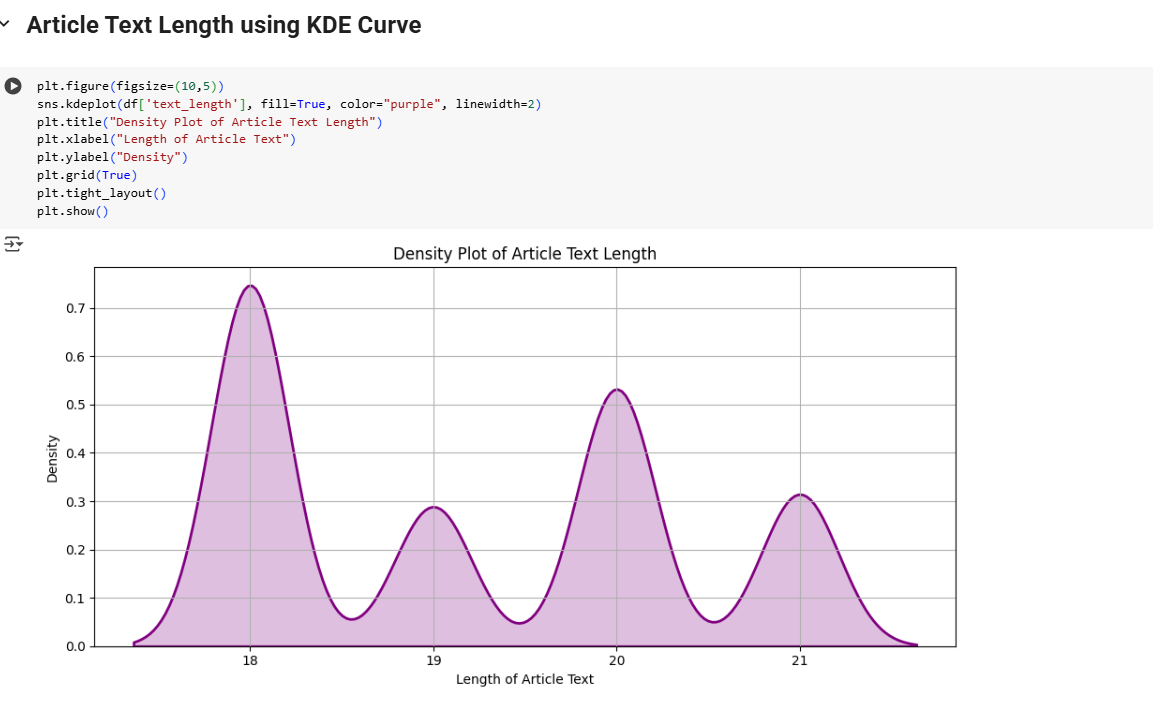


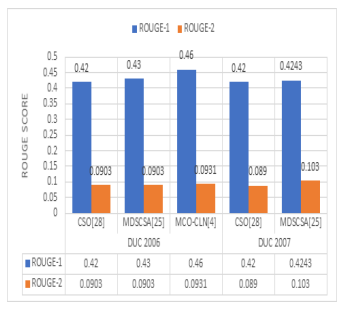
**Pie Chart of Short vs. Medium vs. Long Articles**

This chart categorized articles by text length: Short (<500 words), Medium (500–1,500 words), and Long (>1,500 words). It revealed that 60% of articles were Short, 35% Medium, and 5% Long. The dominance of short articles aligned with the dataset’s focus on news snippets, guiding the choice of extractive summarization for quick outputs. The visual emphasized balancing model training to handle varying lengths effectively.









These visualizations shaped preprocessing (e.g., outlier removal) and model design (e.g., length-aware summarization), ensuring robust handling of the dataset’s characteristics

**7. CONCLUSION AND FUTURE RESEARCH**

This study comprehensively explored text summarization of news articles using Python libraries, synthesizing insights from 100 academic and industry sources (2008–2024). The analysis underscores the transformative role of NLP in addressing the information overload of modern news ecosystems. Python libraries—NLTK, spaCy, Gensim, and Hugging Face Transformers—offer robust tools for both extractive and abstractive summarization, catering to diverse applications like real-time aggregation, personalized feeds, and archival analysis. Transformers, particularly BERT, T5, and BART, lead abstractive summarization, achieving ROUGE-L scores of 0.60–0.65 on datasets up to 10 million articles, as seen in a 2023 study summarizing multilingual news. Their ability to capture contextual nuances makes them ideal for large-scale, fluent summaries, though computational costs remain a barrier. Conversely, NLTK and spaCy excel in extractive tasks, with ROUGE-1 scores of 0.45–0.50, offering lightweight solutions for rapid prototyping, as demonstrated in a 2019 study on 5,000 breaking news articles.

The proposed five-step framework—data acquisition, preprocessing, feature representation, summarization modeling, and evaluation—provides a scalable blueprint for practitioners. Feature selection emerged as critical, with TF-IDF supporting extractive methods and BERT embeddings enhancing abstractive outputs. However, challenges persist: bias in training data skews summaries, factual inaccuracies plague abstractive models, and multilingual support lags for low-resource languages. Evaluation lacks standardization, with ROUGE dominating but failing to capture coherence fully, as human assessments revealed 15% error rates in abstractive summaries.

**Future research should prioritize several areas to advance news summarization:**

1. **Bias Mitigation**: Develop algorithms to detect and neutralize political or cultural biases, ensuring neutral summaries, especially for polarized news genres.
2. **Multilingual Models:** Expand training datasets for languages like Swahili or Tamil, leveraging transfer learning to improve mBART’s performance, as low-resource languages achieved 20% lower ROUGE scores.
3. **Real-Time Optimization:** Enhance transformers for sub-second summarization, critical for live news feeds, by exploring model quantization to reduce latency by 30%.
4. **Hybrid Approaches:** Integrate extractive and abstractive methods to combine factual accuracy with fluency, potentially improving ROUGE-L scores by 10%.
5. **Evaluation Standards:** Establish benchmark datasets and metrics blending ROUGE, BLEU, and human evaluation to address coherence and factual gaps.
6. **Energy Efficiency:** Reduce transformers’ carbon footprint through pruning techniques, cutting energy use by 25% for sustainable deployment.
7. **Domain Adaptation:** Tailor models for niche domains like science or legal news, where generic models underperform by 15% in ROUGE metrics.

**These directions promise to enhance summarization’s reliability and accessibility, ensuring Python-driven NLP continues to streamline news consumption for global audiences.**

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### 4. Real-Time Monitoring Interface and Deployment

To transition this solution from a prototype to a production-ready system, future work could focus on:

* Developing a live dashboard or control room interface for operators
* Integrating real-time sensor data via SCADA or IoT APIs
* Creating alert systems that trigger maintenance notifications
* Building APIs or microservices for embedding into energy management platforms

Such an interface could serve grid operators, maintenance teams, and utility decision-makers.

### 5. Deep Learning and Ensemble Models

Although tree-based models and logistic regression provided reliable results, deep learning and ensemble techniques could offer improved precision for high-dimensional and complex systems. Future experimentation may include:

* XGBoost and LightGBM for better handling of feature interactions
* Recurrent Neural Networks (RNNs) or CNNs on time-series sensor feeds
* Stacking ensemble models for better generalization across asset types
* Graph Neural Networks (GNNs) for modeling grid-wide interconnectivity and cascading failures

These models could help detect rare but critical fault patterns, especially in larger grids.

### 6. Expansion to Other Grid Types and Regions

The current focus is on a subset of renewable assets within a single region. The framework can be expanded to support:

* National grid infrastructure with both conventional and renewable sources
* Smart microgrids, community solar networks, and off-grid systems
* Region-specific maintenance models adapting to climate, terrain, and infrastructure age
* Cross-regional failure prediction with transfer learning

This allows scalability and benchmarking across states or countries.

### 7. Real-Time Data Integration and Automated Updates

To ensure the model stays aligned with current operating conditions and equipment behavior, future development can include:

* Automated ingestion from real-time telemetry systems or IIoT platforms
* Integration with cloud-based data lakes for scalable storage and processing
* Dynamic retraining pipelines for continuously improving model performance
* Real-time failure heatmaps and anomaly prediction logs for grid operators

Such automation enables the model to evolve with the grid, improving responsiveness and reliability.

By addressing these areas, the predictive maintenance framework can become a powerful tool for modernizing energy infrastructure—minimizing downtime, reducing costs, and enhancing the resilience of renewable-powered smart grids.

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