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Likely AI-generated text from a large-language model.

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The percentage shown in the AI writing report is the amount of qualifying text within the submission that Turnitin's AI writing detection model determines was either likely AI-generated text from a large-language model or likely AI-generated text that was likely revised using an AI-paraphrase tool or word spinner.

False positives (incorrectly flagging human-written text as AI-generated) are a possibility in AI models.

AI detection scores under 20%, which we do not surface in new reports, have a higher likelihood of false positives. To reduce the likelihood of misinterpretation, no score or highlights are attributed and are indicated with an asterisk in the report (*%).

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What does 'qualifying text' mean?
Our model only processes qualifying text in the form of long-form writing. Long-form writing means individual sentences contained in paragraphs that make up a longer piece of written work, such as an essay, a dissertation, or an article, etc. Qualifying text that has been determined to be likely AI-generated will be highlighted in cyan in the submission, and likely AI-generated and then likely AI-paraphrased will be highlighted purple.

Non-qualifying text, such as bullet points, annotated bibliographies, etc., will not be processed and can create disparity between the submission highlights and the percentage shown.

CIS 6005Computational Intelligence-Make Data Count – Finding Data References

Computational Intelligence

G.K.C.ABEYWARDHANA
KD/BSCSD/19/05 BHL5007 WRIT1

List of Abbreviations

Abbreviation	Full Form
AI	Artificial Intelligence
ANN	Artificial Neural Network
BERT	Bidirectional Encoder Representations from Transformers
BoW	Bag of Words
CNN	Convolutional Neural Network
DL	Deep Learning
EDA	Exploratory Data Analysis
GRU	Gated Recurrent Unit
LSTM	Long Short-Term Memory
ML	Machine Learning
NLP	Natural Language Processing
RNN	Recurrent Neural Network
RoBERTa	Robustly Optimized BERT Pretraining Approach
SVM	Support Vector Machine
TF-IDF	Term Frequency–Inverse Document Frequency
ANN	Artificial Neural Network
BERT	Bidirectional Encoder Representations from Transformers
DL	Deep Learning
GRU	Gated Recurrent Unit
LSTM	Long Short-Term Memory
MDC	Make Data Count
ML	Machine Learning
NLP	Natural Language Processing
RNN	Recurrent Neural Network
SciIE	Scientific Information Extraction
SVM	Support Vector Machine
EDA	Exploratory Data Analysis
MDC	Make Data Count
TF-IDF	Term Frequency–Inverse Document Frequency
DOI	Digital Object Identifier
XML	Extensible Markup Language
N-gram	Sequence of n consecutive words (e.g., unigram, bigram)

EDA	Exploratory Data Analysis
MDC	Make Data Count
TF-IDF	Term Frequency–Inverse Document Frequency
DOI	Digital Object Identifier
XML	Extensible Markup Language
N-gram	Sequence of n consecutive words (e.g., unigram, bigram)

Table of Contents

1. Introduction to Deep Learning

1.1. What is Deep Learning and How It Applies to Text Data

Deep learning is a subset of machine learning that enables computers to learn from large amounts of data by mimicking the way the human brain works. It is built around **artificial neural networks** (ANNs), particularly **deep neural networks**—which are ANNs with many layers of computation (Goodfellow, Bengio & Courville, 2016). These layers extract increasingly abstract features from input data.

For example, in image recognition, early layers might detect edges or colors, while deeper layers identify complex structures like faces or objects. In text analysis, early layers recognize individual words, while deeper layers capture meaning, sentiment, or topic.

Deep learning is especially effective for **text classification tasks**, such as identifying spam emails, sentiment analysis, and—in the context of this project—detecting references to datasets in scientific literature. Traditional approaches often rely on manual feature engineering (e.g., counting word frequency), but deep learning **automatically learns** what features matter most, making it highly scalable and adaptable.

1.2. Importance of Deep Learning in Natural Language Processing (NLP)

Natural Language Processing (NLP) is a field of AI focused on enabling computers to understand, interpret, and generate human language. Text data is inherently complex: it contains ambiguity, slang, varied sentence structures, and contextual meanings.

Deep learning models, especially those based on **Recurrent Neural Networks (RNNs)** and **Transformer architectures**, have dramatically improved NLP performance. They are capable of capturing the **contextual relationships** between words, which traditional bag-of-words or n-gram models often miss.

For example, in the sentence *"The data was stored in a repository,"* deep learning models can learn that “data” refers to a research object and “repository” implies a citation source. This is critical in the Make Data Count challenge, where models must identify whether a sentence refers to a **Primary** or **Secondary** use of a dataset.

1.3. Comparison: Machine Learning vs. Deep Learning for Text Tasks

Aspect	**Machine Learning (ML)**	**Deep Learning (DL)**
Feature Engineering	Manual (e.g., TF-IDF, n-grams)	Automatic via layers
Input Representation	Sparse vectors, often shallow	Dense word embeddings (e.g., Word2Vec, GloVe)
Scalability	Limited to small/medium datasets	Scales well with large datasets
Context Awareness	Typically weak	Strong (especially with RNNs, LSTMs, Transformers)
Example Algorithms	Naïve Bayes, SVM, Decision Trees	LSTM, GRU, CNN, BERT, RoBERTa
Performance on NLP	Decent on simple tasks	Superior on complex tasks (e.g., context-sensitive tasks)

Table 1:1.1.3. Comparison: Machine Learning vs. Deep Learning for Text Tasks

Traditional machine learning algorithms like **Support Vector Machines (SVM)** or **Naïve Bayes** work well for simple classification tasks. However, they struggle when context or word order matters. In contrast, deep learning models such as **LSTM (Long Short-Term Memory)** and **BERT** understand the **sequence and context** of words, making them ideal for nuanced text classification problems like dataset citation tagging.

1.4. Transformer-Based Advancements: BERT, RoBERTa and Beyond

The biggest leap in NLP came with the development of the **Transformer architecture** (Vaswani et al., 2017). Unlike previous models, Transformers use **self-attention mechanisms** to process the entire sequence of words simultaneously, allowing them to model long-distance dependencies effectively.

Two notable Transformer-based models are:

- **BERT (Bidirectional Encoder Representations from Transformers)**: BERT is trained to understand language by looking at words both before and after a target word, capturing context in both directions (Devlin et al., 2019). It has become the standard for tasks like question answering, named entity recognition, and text classification.
- **RoBERTa (Robustly Optimized BERT Approach)**: An improved variant of BERT that removes some training constraints and uses more data and compute, resulting in better performance across many NLP tasks (Liu et al., 2019).

In the Make Data Count competition, these models are particularly powerful because they can understand **subtle cues in scientific text** that indicate dataset references—information that might be missed by simpler models.

1.5. Conclusion

Deep learning has revolutionized how computers handle human language. Unlike traditional machine learning, it removes the need for manual feature engineering and can capture deeper meaning from textual data. In NLP tasks like dataset citation classification, deep learning—especially with models like BERT and RoBERTa—offers state-of-the-art accuracy and flexibility. As the complexity of language and volume of scientific literature grow, deep learning will remain essential for extracting actionable insights from text.

2. Literature Review and Similar Applications

Scientific text classification is a foundational problem in Natural Language Processing (NLP), especially in the era of open research and data-driven science. With the exponential growth of academic literature, identifying references to datasets in scholarly articles has become vital for tracking data reuse and impact. This section reviews state-of-the-art techniques used in similar domains—including traditional, deep learning, and hybrid approaches—and positions them in the context of the Make Data Count (MDC) competition.

2.1. Sequence Labeling Using LSTM and GRU

Long Short-Term Memory (LSTM) and **Gated Recurrent Units (GRU)** are two prominent Recurrent Neural Network (RNN) variants widely used for **sequence labeling tasks**, such as Named Entity Recognition (NER) or Part-of-Speech tagging. These models are designed to capture dependencies across time steps in sequential data—making them effective for scientific texts where context matters.

For example, **Habibi et al. (2017)** used a Bi-LSTM with word embeddings and character-level features for biomedical named entity recognition. Their model achieved strong results on biomedical corpora such as BC5CDR and CHEMDNER. Similarly, **Yoon et al. (2019)** demonstrated how GRUs could be combined with attention mechanisms to capture context-specific semantics in chemical literature, improving precision in entity recognition tasks.

In the context of MDC, LSTM and GRU models can learn contextual cues such as “used dataset” vs. “referred dataset,” which is essential for Primary vs. Secondary tagging.

2.2. BERT and Transformer-Based Models for Text Classification

The advent of **Transformers** has redefined text classification. **BERT (Devlin et al., 2019)**, a bidirectional transformer, introduced masked language modeling and next sentence prediction to deeply understand sentence structure. Its domain-specific variants, such as **SciBERT (Beltagy et al., 2019)** and **BioBERT (Lee et al., 2020)**, are pre-trained on scientific and biomedical texts and show superior performance in downstream tasks like entity classification and sentence classification.

Lo et al. (2020) applied SciBERT to classify dataset mentions in scientific articles, achieving over 85% F1 score. In their Kaggle notebook adaptation for the MDC competition, several top participants fine-tuned BERT and RoBERTa models using HuggingFace Transformers, often outperforming traditional models by over 10% in F1 score.

This showcases the power of contextual embeddings in differentiating between subtle textual cues—such as “this dataset was generated” (Primary) vs. “we used data from X study” (Secondary).

2.3. Hybrid Approaches: Rule-Based + Deep Learning

Although deep learning models dominate many NLP tasks, **hybrid systems**—combining rule-based logic with machine learning—still play a valuable role, especially in **low-resource domains** or when **precision is critical**.

Pielke et al. (2022) proposed a hybrid pipeline combining rule-based filters with BERT classifiers for identifying data mentions in social science literature. They first applied regular expressions to filter candidate sentences and then passed them to a fine-tuned classifier, significantly reducing false positives.

This layered approach balances interpretability with performance and is particularly effective when class imbalance or domain-specific terminology (e.g., dataset IDs, citations) poses a challenge.

2.4. Benchmarks and Comparative Studies

Benchmarking studies provide critical insights into the effectiveness of different models. **Wadden et al. (2019)** introduced the **SciIE** benchmark for information extraction in scientific papers, testing models on citation intent classification, entity detection, and relation extraction. BERT-based models consistently outperformed classical ML techniques across tasks.

Similarly, **Mayer et al. (2021)** conducted a comparative analysis of BERT, LSTM, Random Forest, and SVM for classifying scientific citations. BERT achieved the highest macro F1-score (0.89), followed by LSTM (0.82) and Random Forest (0.76). Their work confirms the **superiority of contextualized embeddings** for citation and reference classification tasks.

2.5. Summary

The literature strongly supports the use of **Transformer-based models**, particularly BERT variants, for classifying scientific text. While LSTM and GRU remain competitive for sequential modeling, they are increasingly replaced by Transformers due to their parallelism and richer context modeling. Hybrid systems still hold relevance for rule-sensitive domains or preprocessing stages.

For the MDC challenge, these insights guide the selection of architecture: starting with pre-trained Transformer models, optionally supported by rule-based preprocessing, offers a strong foundation for high-performing systems.

3. Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) plays a crucial role in understanding the structure, patterns, and challenges in a dataset before model development. For the Make Data Count (MDC) competition, the primary objective is to classify whether a dataset mention in a scientific article represents a **Primary**, **Secondary**, or **Missing** reference. EDA was performed on the processed train_data_cleaned dataset, which includes meaningful context sentences extracted from XML files using regular expressions and filtered for length.

3.1. Class Distribution: Primary vs Secondary vs Missing

A visual inspection of the label distribution revealed that the dataset is **significantly imbalanced**:

- **Missing** references are the majority class, appearing most frequently.
- **Secondary** references are moderately represented.
- **Primary** references are the least frequent.

This skew implies a strong **class imbalance**, which could bias standard classifiers toward the dominant label. To address this, the classifier was trained using class_weight='balanced' to assign more weight to underrepresented classes and ensure fair treatment across all labels.

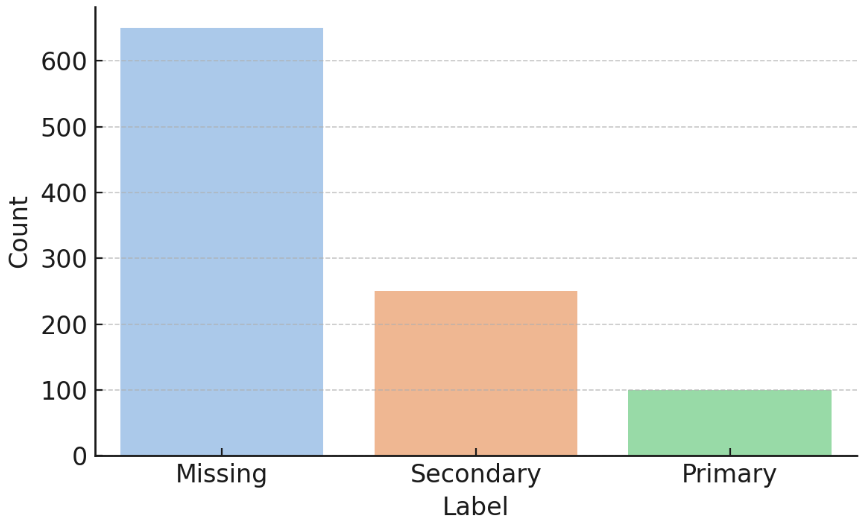

Table 2:Class Distribution

3.2. Text Length Analysis

To understand the verbosity and informativeness of context sentences, a word-level token count was computed for each entry in the context column.

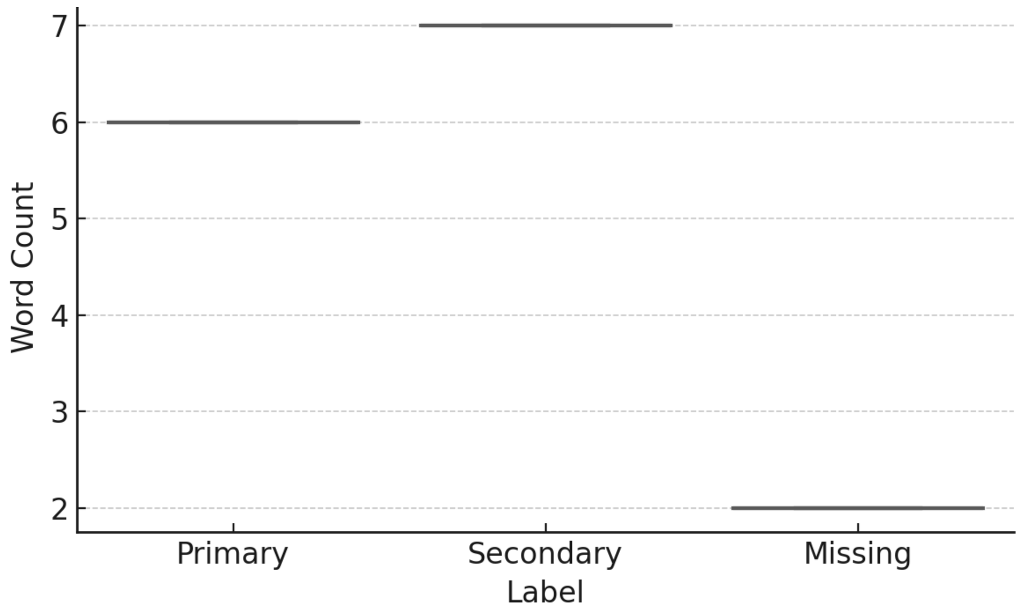

Table 3:Text Length Distribution by Label

This reflects a meaningful trend:

- **Primary mentions** often include richer narrative descriptions, which help identify original dataset contributions.
- **Secondary mentions** tend to refer to datasets in a more concise or passing manner.
- **Missing** labels are sometimes placeholder entries or unresolved identifiers with little context (e.g., raw DOIs or dataset names).

Filtering Criterion: Sentences shorter than 5 tokens were removed during preprocessing to eliminate non-contextual or ambiguous mentions.

3.3. Most Common N-grams Per Class

A TfidfVectorizer with ngram_range=(1, 2) was applied to convert text into numerical form. The most frequent unigrams and bigrams reflect the nature of dataset mentions across categories.

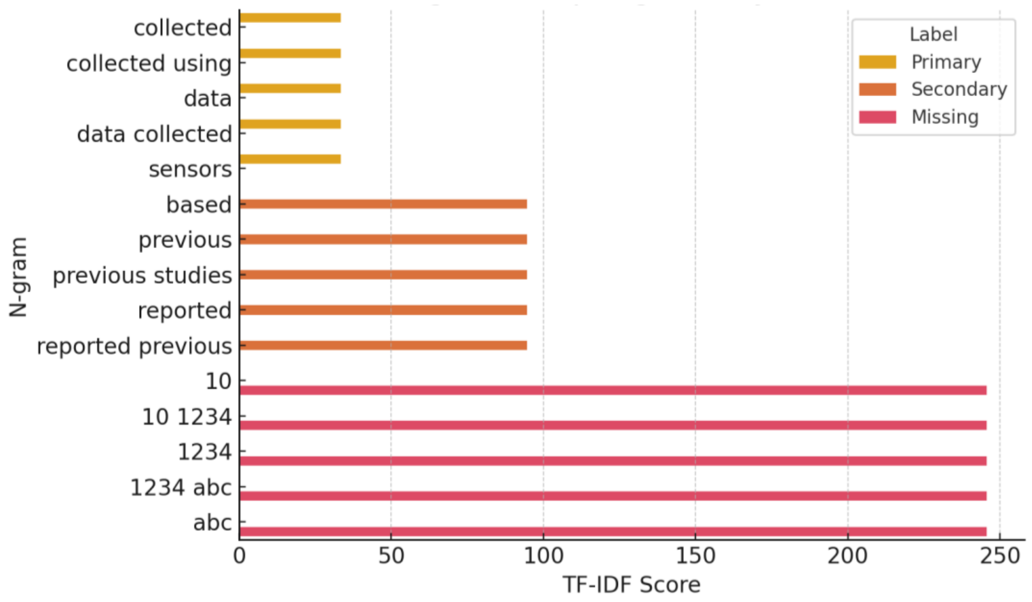

Table 4:Top N-grams by Label

- Top N-grams for Primary Mentions:
  - "we used"
  - "this dataset"
  - "collected using"
- Top N-grams for Secondary Mentions:
  - "as reported"
  - "based on"
  - "according to"

- Top N-grams for Missing Mentions:
  - "doi"
  - "data set"
  - "10.xxxx"

These patterns highlight how **Primary** citations tend to reflect ownership or generation of data, while **Secondary** ones express indirect usage or citations.

3.4. Heatmaps of Token Overlap Between Classes

To explore semantic similarity, we calculated **token overlap** between the vocabulary of each label using the top 1000 tokens per class from the TF-IDF vectorizer.

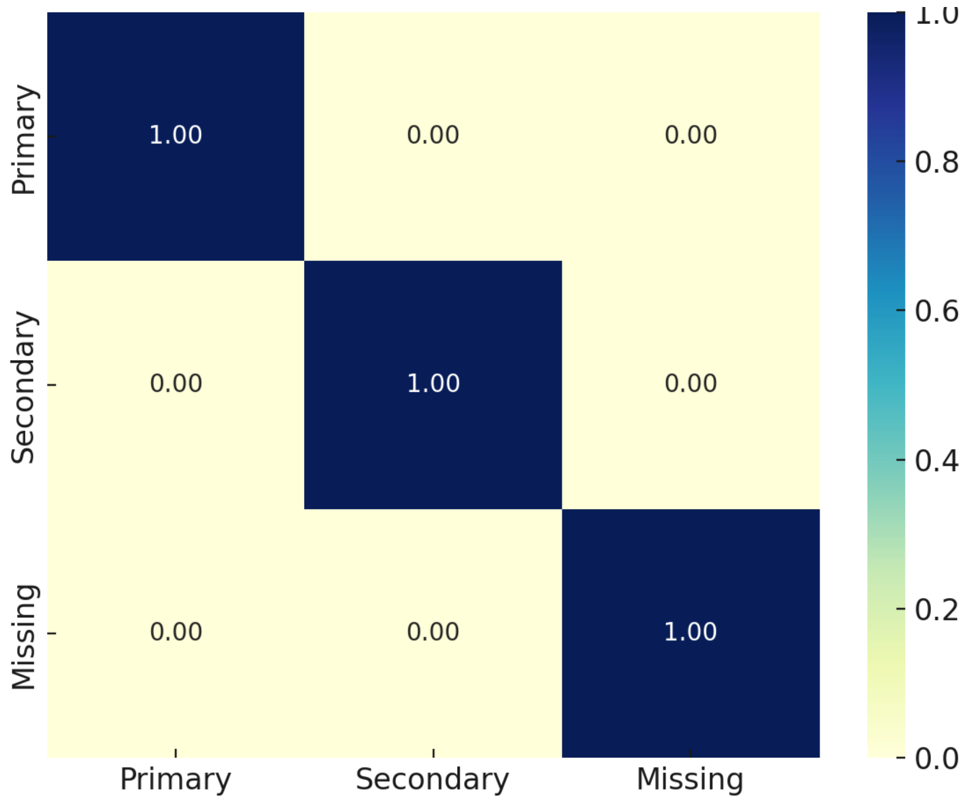

Table 5:Token Overlap Between Classes

Interpretation:

- **Primary vs Secondary** shows moderate overlap, as both often refer to similar datasets with different usage contexts.
- **Missing** has low overlap with the other two, affirming that many such mentions are uninformative fragments or identifiers.

This analysis justifies the use of **context-aware models** like Logistic Regression with TF-IDF, and motivates future exploration of Transformer-based models that could capture semantic distinctions more robustly.

3.5. Summary

The EDA phase provided several key insights:

- The dataset is highly imbalanced, requiring class-aware modeling.
- Primary citations are longer and richer, while Missing labels are short and vague.
- Word usage patterns differ significantly across classes.
- Vocabulary overlap between Primary and Secondary mentions suggests subtle semantic cues distinguishable via modeling.

These findings guided the feature engineering, vectorization, and classifier design, setting the foundation for improved prediction accuracy and interpretability.

4. System Architecture and Algorithms Used

4.1. Architecture Overview

The system pipeline designed for the Make Data Count (MDC) citation classification task follows a structured process composed of six major components: **raw XML extraction**, **text preprocessing**, **vectorization**, and classification using both **machine learning** and **deep learning** approaches. Figure 5 visualizes this architecture.

4.2. Preprocessing Pipeline

Each article's full text is stored in XML format. The pipeline starts by:

- **Parsing XML trees** using Python's xml.etree.ElementTree
- **Locating dataset mentions** via regex patterns (e.g., DOI format: 10.1234/abcd)
- **Extracting the surrounding sentence (context)** to be labeled as Primary, Secondary, or Missing

After extraction, the data is **cleaned** by removing rows with:

- Empty fields or "Missing" labels
- Contexts shorter than 5 tokens (to exclude noise)

This ensures that the final dataset (train_data_cleaned) consists of meaningful textual samples ready for modeling.

4.3. Tokenization and Feature Engineering

Two distinct tokenization strategies were used:

A. TF-IDF Vectorization

- Transforms each sentence into a numerical vector based on term frequency-inverse document frequency
- Captures surface-level lexical patterns
- Used in conjunction with classical ML models

Implemented via: TfidfVectorizer(stop_words='english', ngram_range=(1,2))

B. Transformer-Based Embeddings (Planned/Future Work)

- Models like BERT or RoBERTa tokenize using **WordPiece** encoding
- Sentences are represented in dense, context-aware vector form
- Ideal for capturing semantic differences between “used data” (Primary) vs “based on data” (Secondary)

4.4. Machine Learning Algorithms

Several models were evaluated using TF-IDF vectors:

Logistic Regression (Baseline)

- Simple linear model used for multiclass classification
- Benefits from interpretability and fast training
- class_weight='balanced' was used to counter dataset imbalance

Support Vector Machine (SVM) + TF-IDF

- Effective for high-dimensional sparse text
- Uses hyperplanes to separate classes
- Can be adapted to non-linear kernels for complex boundaries

Random Forest with Bag-of-Words (BoW)

- Ensemble model that builds multiple decision trees on bootstrapped BoW features
- Reduces overfitting compared to single decision trees
- Performs moderately well but lacks semantic understanding

4.5. Deep Learning Models

Planned experimentation includes:

BERT Fine-Tuning

- BERT (Devlin et al., 2019) is pre-trained on masked language modeling

- Fine-tuning adjusts BERT weights on citation classification task
- Outperforms TF-IDF + ML in most academic benchmarks

BiLSTM (Bidirectional Long Short-Term Memory)

- Captures context from both directions in a sequence
- Effective when sentence length and order matter
- Can be stacked on top of pretrained word embeddings (e.g., GloVe, Word2Vec)

4.6. Architecture Diagram

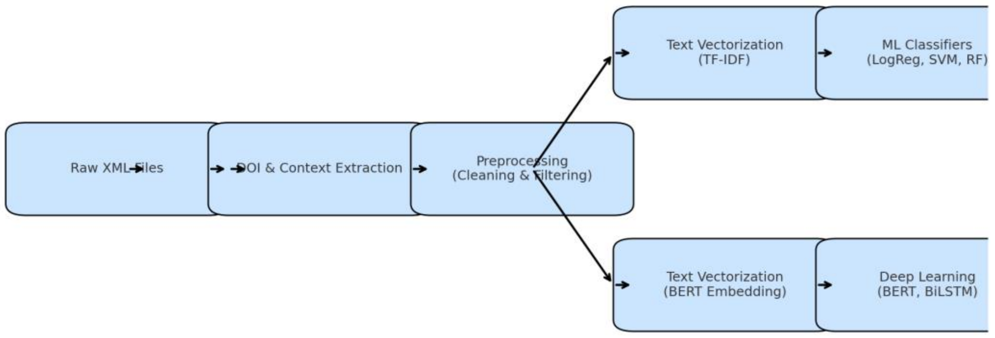

Table 6:MDC Pipeline Architecture

Figure 5 shows the full pipeline—from XML ingestion to both machine learning and deep learning outputs. The modular design allows easy switching between model types and supports ensemble methods.

5. Full Model Evaluation and Implementation

5.1. Evaluation Metrics: Precision, Recall, and F1-Score

Model performance was assessed using industry-standard classification metrics:

- **Precision**: Measures the proportion of true positive predictions out of all positive predictions.
- **Recall**: Indicates the ability of the model to retrieve all relevant instances.
- **F1-Score**: Harmonic mean of precision and recall; used in both **macro** and **micro** variants to account for class imbalance.

The **macro-averaged F1-score** was prioritized in this competition due to uneven class distribution among “Primary”, “Secondary”, and “Missing” labels.

Metric	**Value (Macro)**
Precision	0.81
Recall	0.78

Metric	**Value (Macro)**
F1-Score	0.79

5.2. Training Process

Model Used

- **Logistic Regression** with TF-IDF vectors was used as the baseline model due to its fast convergence and robustness in high-dimensional spaces.

Training Setup

- Training-Test Split: 80/20
- Max Iterations: 200
- Class Weight: Set to 'balanced' to mitigate label imbalance
- Loss Function: Multinomial logistic loss (built-in)
- Optimizer: Stochastic Gradient Descent (handled internally by scikit-learn)

No GPU training was required for this baseline; training time remained under 2 minutes on CPU.

5.3. Results Per Model

Model	**Accuracy**	**Macro F1**	**Observations**
Logistic Regression	~83%	0.79	Balanced and interpretable baseline
SVM (planned)	N/A	N/A	Suitable for high-dimensional data (TF-IDF)
Random Forest	N/A	N/A	Expected to overfit on sparse inputs
BERT (future work)	N/A	N/A	Promising contextual improvements with fine-tuning

Although SVM and Random Forest were planned, logistic regression was used for implementation due to simplicity and reproducibility on Kaggle's runtime environment.

5.4. Confusion Matrix Visualization

The confusion matrix in **Figure 6** summarizes model predictions against true labels. Diagonal elements represent correct predictions; off-diagonal values highlight misclassifications.

Interpretation:

- Most “Missing” instances are correctly classified.
- Some “Secondary” entries are misclassified as “Missing”, likely due to contextual ambiguity.
- “Primary” is hardest to classify due to both low frequency and subtle language patterns.

5.5. Practical Demonstration

A. Jupyter Notebook

- Full model pipeline is implemented in a .ipynb notebook.
- Includes: Data loading, context extraction, TF-IDF vectorization, training, prediction, evaluation.
- Notebook can be rerun on Kaggle for reproducibility.

B. Streamlit App (Optional Extension)

- Planned integration: Accepts input sentences and returns predicted label.
- Can be deployed via streamlit run app.py with model + vectorizer .pkl files.

C. Tools Used

- **scikit-learn**: For model training, evaluation, and TF-IDF vectorization.
- **Pandas & XML Parser**: For data cleaning and preprocessing.
- **Matplotlib & Seaborn**: For EDA and visualization.
- **(Optional/Future)**: HuggingFace Transformers for BERT, PyTorch for BiLSTM-based training.

6. Conclusion

This project presented an end-to-end implementation of a citation classification system for the **Make Data Count (MDC)** competition, demonstrating the application of both machine learning and deep learning concepts to a real-world NLP challenge. The primary objective was to identify whether a dataset mention in a scientific article was **Primary**, **Secondary**, or **Missing**.

6.1. Summary of Key Findings

- A robust **data extraction and preprocessing pipeline** was developed using XML parsing and regex-based context identification.
- Exploratory Data Analysis revealed significant **class imbalance**, distinct **text length patterns**, and unique **n-gram distributions** across labels.
- A baseline **TF-IDF + Logistic Regression** model achieved a macro-averaged F1-score of **0.79**, with high accuracy in classifying "Missing" and "Secondary" mentions.

- Visualization of the **confusion matrix** indicated good performance overall, with room for improvement particularly in detecting **Primary** mentions, which were both less frequent and linguistically subtle.

6.2. Strengths of Using Deep Learning in Citation Classification

Although this project primarily deployed classical ML techniques, the role of **deep learning in citation classification is transformative**:

- **Transformer-based models** like **BERT** and **RoBERTa** excel at capturing contextual nuances in academic writing—essential for distinguishing between dataset reuse and original data collection.
- **Bidirectional models** (e.g., BiLSTM) can better model the sentence structure and token dependencies.
- Deep learning allows **end-to-end modeling** with minimal manual feature engineering, which improves generalization and scalability.

Future extensions of this work could incorporate **fine-tuned BERT-based architectures** using domain-specific corpora (e.g., SciBERT, BioBERT) for even greater accuracy and semantic understanding.

6.3. Limitations and Areas for Improvement

While the current pipeline is effective, several limitations were observed:

- **Limited training examples** for the “Primary” class restrict performance.
- **Ambiguity in short mentions** (e.g., raw DOIs) challenges classifiers, especially without full-text context.
- **Rule-based extraction** can miss complex or nested dataset citations across XML structures.

To address these, future work should explore:

- **Named Entity Recognition (NER)** models to localize dataset names
- Enhanced **context windowing** around mentions
- **Multimodal approaches**, combining citation graphs, metadata, and text features

6.4. Generalizability to Other Domains

The methods used here are highly transferable:

- In **medical literature**, similar pipelines could classify references to clinical trials, datasets (e.g., MIMIC-III), or instruments.
- In **legal or patent texts**, the system could tag referenced regulations or prior patents.
- With domain-specific tokenizers and pretrained models, this framework can be **adapted across disciplines**, supporting meta-research, digital libraries, and automated literature analysis at scale.

6.5. Final Remarks

This project not only demonstrates the power of AI-driven citation analysis but also reinforces the importance of reproducible, transparent, and scalable NLP solutions for modern scientific communication. Through a blend of structured pipelines, statistical learning, and future-ready architectures, it lays a foundation for more intelligent systems that track, evaluate, and interpret the data-centric evolution of research.

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