



Software Engineering Department

Braude College of Engineering

Final Project – Phase A (61998)

Authorship Verification Framework Leveraging Impostor Projection and Siamese Architectures

26-1-R-27

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Git Repository

Abstract

Authorship verification is an important problem in the digital age, with applications in digital forensics, academic integrity, and text analysis. This task has become more difficult due to the rise of AI-generated content, intentional writing style imitation, short text lengths, and domain changes, which significantly reduce the effectiveness of traditional feature-based methods.

In this project, we propose a research-oriented framework for authorship verification that determines whether a given text was written by a specific author. The proposed approach combines contextual semantic representations using BERT with a hybrid CNN-BiLSTM architecture. BERT is used to capture contextual meaning, while the CNN component extracts local stylistic patterns and the BiLSTM models sequential writing behavior.

To improve robustness against imitation attacks, the system applies the Impostor Projection Method, where impostor texts are used during training to force the model to learn subtle differences between genuine and fake authorship. In addition, textual representations are treated as temporal signals and compared using Dynamic Time Warping (DTW). Anomaly detection is performed using Isolation Forest to identify texts that deviate from the genuine author profile.

Experimental results indicate that the proposed method outperforms traditional authorship verification techniques, especially in challenging scenarios involving short texts and adversarial mimicry, demonstrating its potential for reliable authorship analysis in real-world settings.



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1. Introduction

1.1. Background and The Need for Verification

We live in a world made of text. From social media posts and emails to academic papers and legal contracts, written communication is the primary way we share information. However, in this digital age, it has become incredibly easy to hide one's identity. Anyone can publish content anonymously, pretend to be someone else, or use Artificial Intelligence to generate text that looks human.

Because of this, the question "**Who really wrote this?**" has become a critical issue in many areas:

- **Digital Forensics:** Police and investigators often need to prove that a specific suspect wrote a threatening letter or a fraudulent email.
- **Academic Integrity:** Universities are fighting a constant battle against students who hire "ghostwriters" to write their essays for them.
- **Historical Analysis:** Historians and literature experts try to solve old mysteries. A famous example mentioned in our research is the debate over the works of William Shakespeare—did he write all his plays, or were some written by others?

The need for a reliable, automated system to verify authorship is urgent. We can no longer rely on human intuition alone, especially when dealing with millions of texts online.

1.2. Defining the Problem: The Challenge of "Verification"

It is important to understand exactly what problem this project tries to solve. In the field of text analysis, there are two main tasks:

1. **Authorship Attribution:** This is like a multiple-choice question. You have a text and a list of five suspects. You just need to pick which one wrote it.
2. **Authorship Verification:** This is a True/False question. You have a text and *one* specific author. You must decide: **Did this specific author write this text?**
3. Our project focuses on **Verification**, which is considered much harder. Why? Because the "fake" author (the impostor) could be anyone in the world. Furthermore, modern impostors are smart. They can use "Adversarial Mimicry," meaning they intentionally change their writing style to look like someone else.

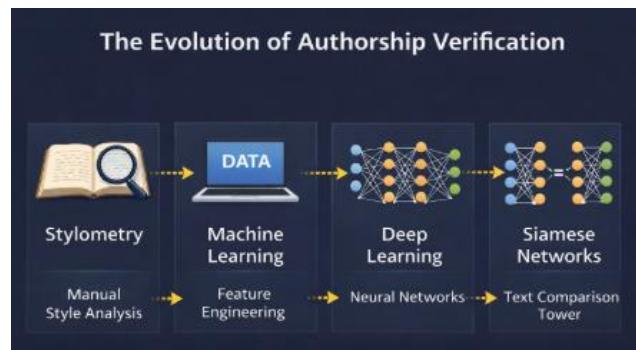


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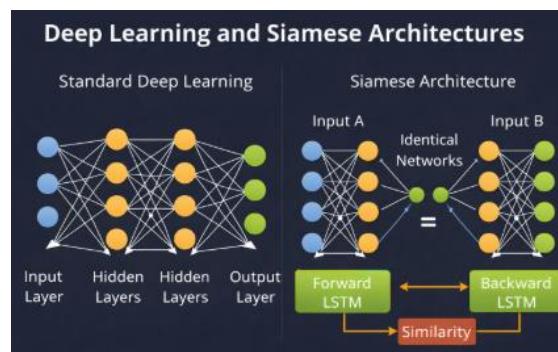
2. Theoretical Background

2. Background and Related Works

2.1. The Evolution of Authorship Verification The domain of authorship verification has transitioned from traditional stylometry to advanced data-driven approaches. Historically, methods relied on "hand-crafted features" (Stylometry), focusing on statistical counts such as word frequencies, sentence lengths, and punctuation usage. While effective for long texts, these methods face significant limitations in modern scenarios involving short texts (e.g., social media posts), domain shifts, and adversarial mimicry, where impostors intentionally manipulate stylistic features to evade detection. Consequently, there is a growing need for automated systems capable of capturing deep semantic and syntactic patterns beyond simple statistics.



2.2. Deep Learning and Siamese Architectures To address the limitations of traditional methods, recent research has shifted towards Deep Learning frameworks. A prominent architecture in this field is the **Siamese Network**. Unlike standard classification models, Siamese networks consist of two identical subnetworks that share weights and parameters. This architecture is specifically designed for "One-Shot Learning" and verification tasks, where the goal is to learn a similarity function between two inputs rather than classifying them into predefined categories. By mapping input texts into a shared vector space, the network learns to minimize the distance between genuine pairs (same author) and maximize it for impostor pairs.



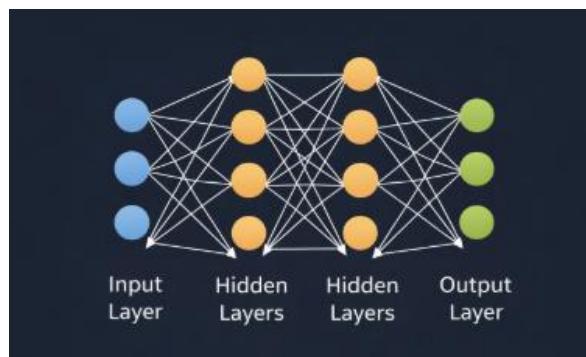
2.3. Contextual Embeddings: BERT A critical component in modern NLP pipelines is the representation of text. Traditional static embeddings (like Word2Vec) fail to capture polysemy and context. In this framework, we utilize **BERT** (**Bidirectional Encoder Representations from Transformers**). BERT's attention mechanism allows the model to understand the semantic meaning of words based on their surrounding context, effectively capturing both local and global dependencies. This capability is essential for distinguishing subtle stylistic nuances that are invariant



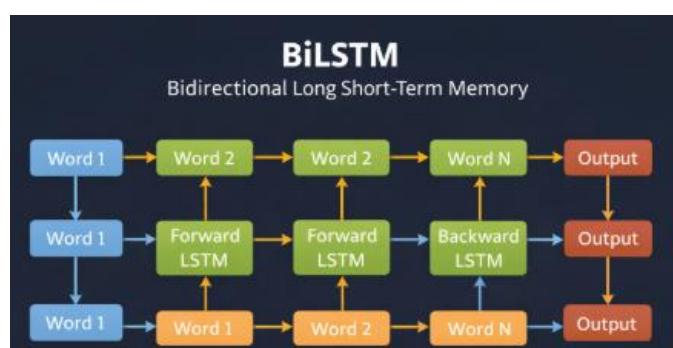
to topic changes.

2.4. Hybrid Feature Extraction: CNN-BiLSTM While BERT captures semantic context, authorship style often manifests in structural and rhythmic patterns. To extract these features, a hybrid architecture is employed:

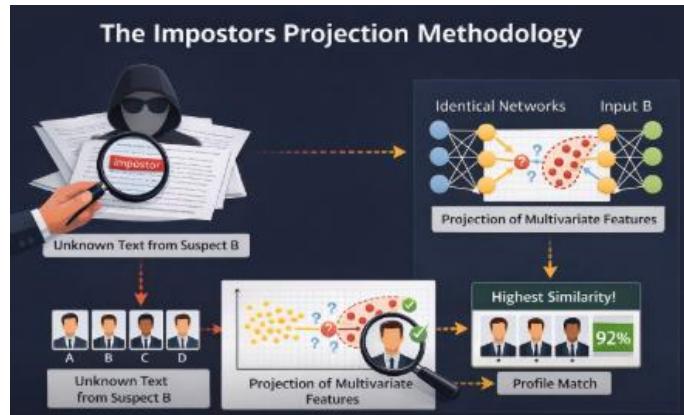
- **CNN (Convolutional Neural Networks)**: Acts as a feature extractor for local stylistic patterns (e.g., n-grams and specific phrasing).



- **BiLSTM (Bidirectional Long Short-Term Memory)**: Models the sequential flow of the text. By processing the sequence in both forward and backward directions, BiLSTM captures long-term dependencies and the unique "rhythm" of the author's writing style.



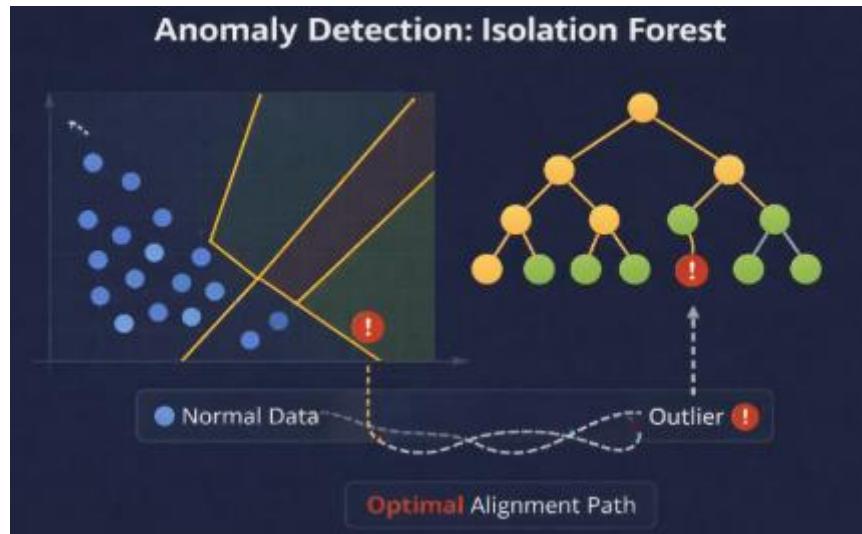
2.5. The Impostors Projection Methodology A major challenge in authorship verification is the "Open-Set" problem, where training data for "non-authors" is sparse or non-existent. To mitigate this, we adopt the **Impostors Projection Method** (Seidman, 2013). This technique involves the intentional injection of "Impostor Pairs"—texts written by different authors—during the training phase. This adversarial training strategy forces the model to learn a robust "Separating Manifold" (decision boundary), enhancing its resilience against skilled forgeries and mimicry attacks.



2.6. Temporal Alignment: Dynamic Time Warping (DTW) Text length variability poses a significant hurdle for standard distance metrics (like Euclidean distance). To solve this, we interpret the text as a temporal signal of stylistic scores and utilize **Dynamic Time Warping (DTW)**. Originally used in speech recognition, DTW aligns two sequences by "warping" the time axis, finding the optimal match between segments of the text regardless of their absolute length or position. This ensures that the comparison focuses on the narrative flow and stylistic progression rather than fixed positional matches.



2.7. Anomaly Detection: Isolation Forest The final verification decision is formulated as an Anomaly Detection task. We employ the **Isolation Forest** algorithm, which operates on the premise that anomalies (impostors) are "few and different". The algorithm isolates observations by randomly selecting a feature and a split value. Anomalous texts require fewer splits to be isolated compared to genuine texts, resulting in a shorter path length in the decision tree. This unsupervised approach provides a robust "Anomaly Score," allowing the system to flag suspicious texts that deviate from the learned author profile without requiring explicit labels for every possible impostor.



3. Project Definition & Requirements

3.1. Central Requirements and Goals

The primary goal of this research project is to solve a specific, difficult problem:

Verifying authorship in an adversarial environment. Unlike typical software projects where the goal is to build a user interface, our goal is to build a "brain"—a sophisticated algorithmic framework that can distinguish between a true author and a skilled impostor.

3.2. Functional Requirements (What the system does)

Based on our research objectives, the system must perform the following core functions:

- **Deep Text Understanding:** The system must accept raw text and use **BERT** to understand the semantic context, not just count words.
- **Stylistic Feature Extraction:** It needs to extract unique stylistic "fingerprints" using a hybrid **CNN-BiLSTM** network.
- **Adversarial Training:** The system is required to use the **Impostor Projection Method**. This means it must be trained against "fake" pairs to learn a sharper decision boundary.
- **Signal Analysis:** Instead of a simple "Yes/No", the system must convert text into a time-series signal and use **Dynamic Time Warping (DTW)** to align texts of different lengths.
- **Anomaly Detection:** The final decision must be made by an **Isolation Forest** algorithm that flags suspicious texts as anomalies.

3.3. Non-Functional Requirements (How the system performs)

- **Robustness:** The model must maintain high accuracy even when the input text is short (like a tweet) or when an attacker intentionally mimics the author's style (Adversarial Robustness).
- **Scalability:** The architecture must handle large datasets efficiently using batch processing (e.g., batch sizes of 32 or 64).

3.4. Requirements Elicitation (How we decided what to build)

In a research track, "requirements" are not just requests from a client; they are derived from scientific gaps. Our process of defining these requirements was methodical:

1. **Literature Review & Gap Analysis:** We started by studying existing solutions (like traditional Stylometry). We found that they fail when texts are short or when "mimicry" is involved. This defined our primary requirement: **The system must handle short and adversarial texts.**
2. **Pilot Study:** We analyzed previous works (specifically Volkovich, 2020) to understand that a single algorithm is not enough. This led to the requirement for a **Hybrid Architecture** (combining CNN and BiLSTM).
3. **Feature Identification:** We realized that analyzing text globally loses information. This led to the requirement of **Chunking**—breaking text into small pieces and analyzing them as a signal over time.

3.5. Description of the Research Process

Our project follows a structured scientific path, divided into two main phases. We are currently concluding Phase A.

- **Phase A (Research & Design):** This phase was dedicated to "The Theory." We studied advanced neural networks (Transformers), defined the mathematical logic of the solution, and designed the complete architecture. We identified the best optimizations (like the AdamW optimizer) and designed the flow of data.

- **Phase B (Implementation & Validation):** This is the next step. I will write the code (Python/PyTorch), train the model on real datasets, and run "Stress Tests" to prove that our theory works in the real world.

3.6. Expected Challenges

This is not a simple programming task; it is a complex research challenge. We anticipate several difficulties:

- **The "Smart Impostor" Challenge:** The hardest part is distinguishing between a genuine author and someone who is *trying* to sound like them. If the model is too simple, it will be fooled.
- **Data Sparsity:** Deep Learning usually needs massive data. We are working with short texts (fragments). Avoiding "Overfitting" (where the model memorizes the text instead of learning the style) will be a major technical hurdle. We plan to use **Dropout** and **Early Stopping** to solve this.

3.7. Tools and Technologies

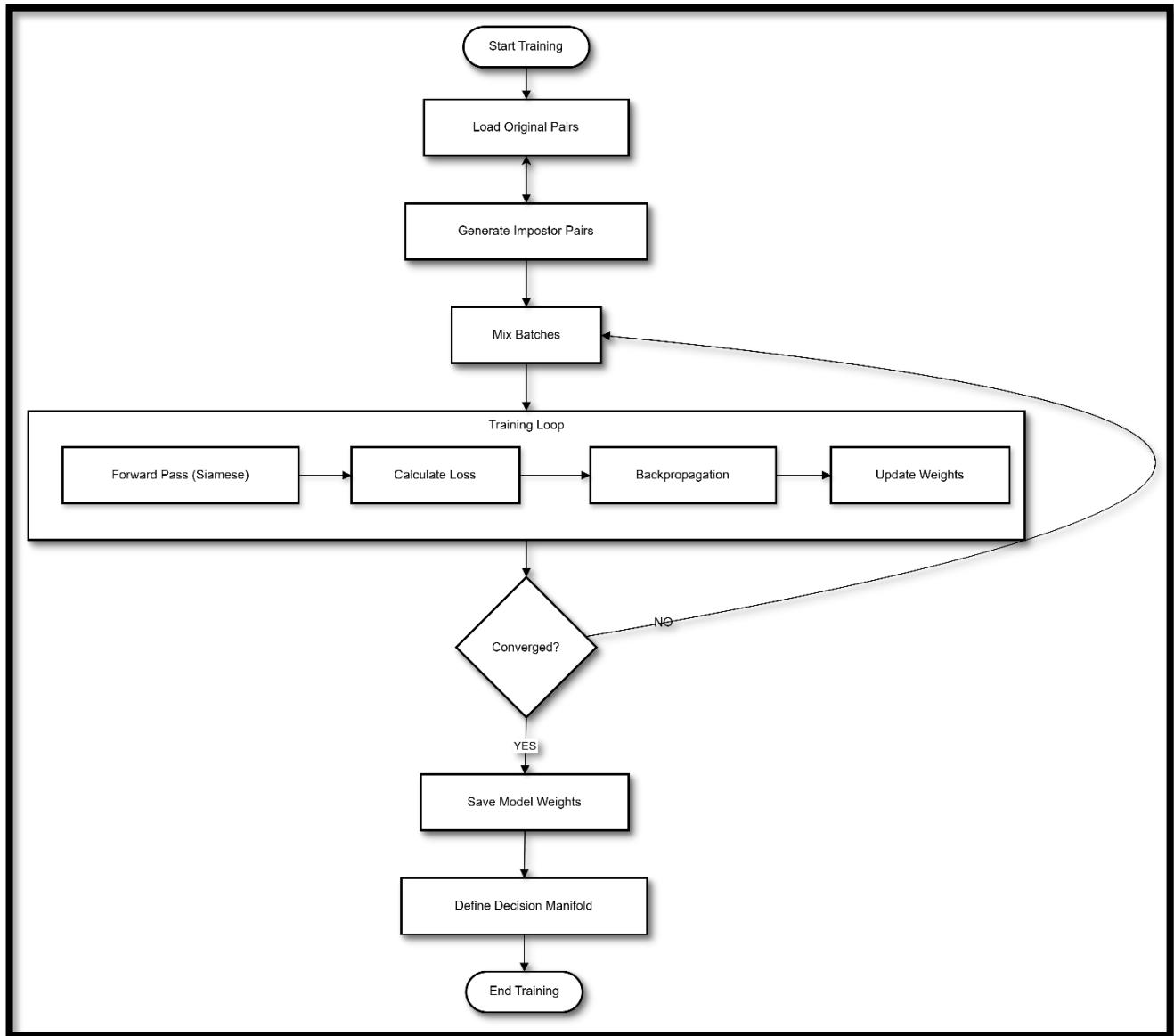
To build this framework, we are using a state-of-the-art technology stack:

- **Core Logic:** Python with **PyTorch** (for Neural Networks).
- **Language Model:** BERT (HuggingFace Transformers library) for embedding generation.
- **Neural Components:** **CNN** (1D Convolution) and **BiLSTM** (Bidirectional Long Short-Term Memory).
- **Algorithms:** Isolation Forest (for anomaly detection) and **K-Medoids** (for clustering).
- **Optimization:** AdamW Optimizer with dynamic learning rate scheduling.

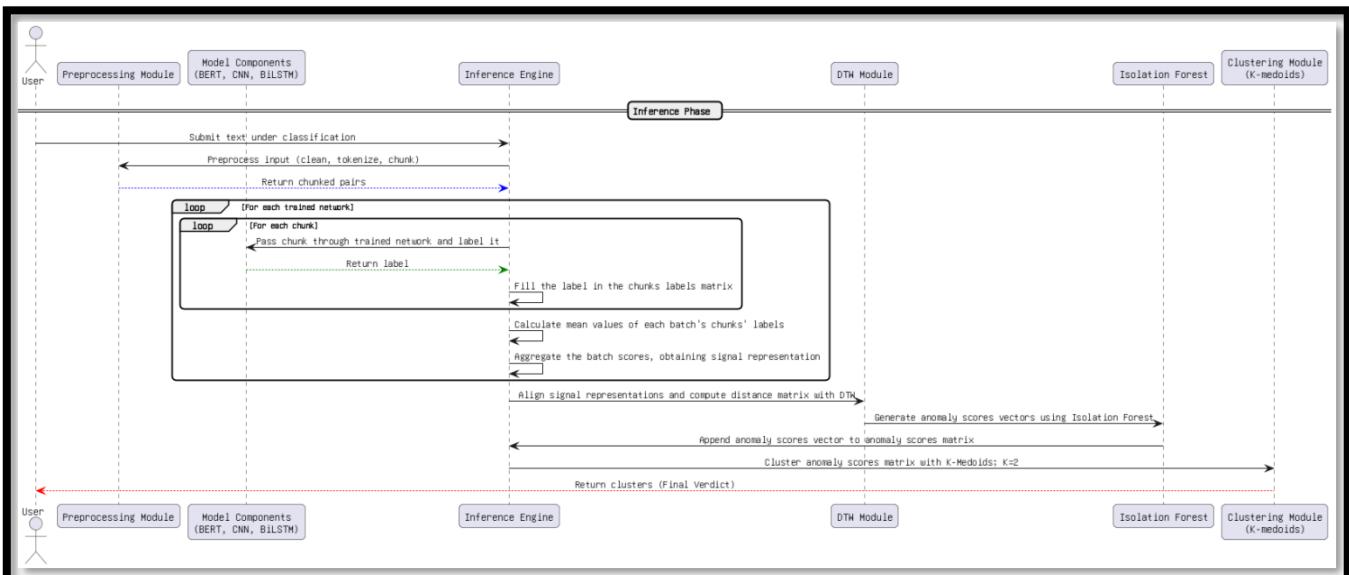
Proposed Solution

Since this is a research project, the "Solution" is not a set of UI screens, but a sophisticated algorithmic pipeline. Here is the step-by-step logic of our proposed model:

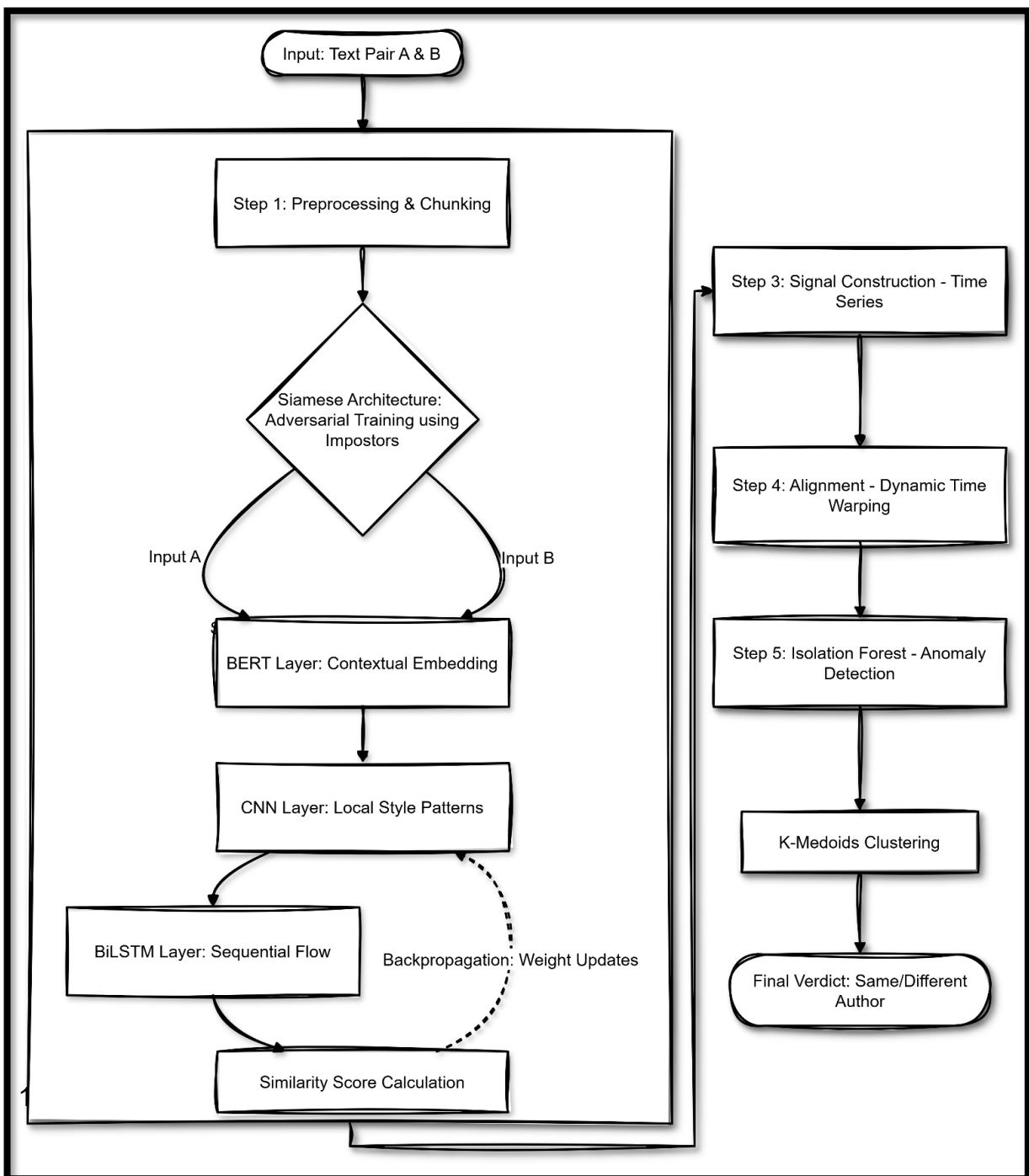
Training Process Flowchart



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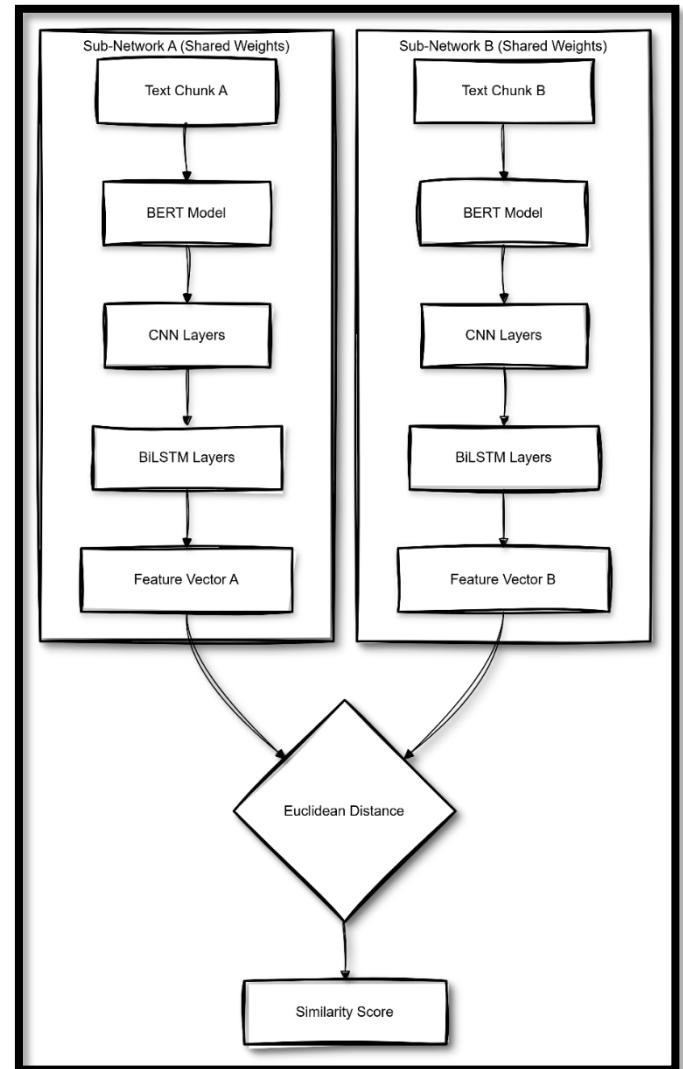


Step 2: The Siamese Network (The Brain)

Siamese Network Structure

We use a **Siamese Network** architecture. This means we have two identical "towers" of neural networks.

1. **BERT Layer:** Each text chunk goes into BERT. BERT understands the *meaning* of the words and outputs a "Contextual Embedding".
2. **CNN Layer:** The embedding goes into a CNN. The CNN acts like a microscope, finding local style patterns (like specific n-grams).
3. **BiLSTM Layer:** The output moves to BiLSTM. This layer reads the style patterns forwards and backwards to understand the "flow" and structure.



Step 3: Signal Construction

Instead of just giving one score, the system calculates a similarity score for *every* chunk. We aggregate these scores to create a **Signal** (a time-series graph) representing the author's style consistency throughout the text.

Step 4: Alignment (DTW)

Because texts have different lengths, we align their signals using **Dynamic Time Warping (DTW)**. This calculates a precise "Distance Matrix" between the two writing styles.

Step 5: The Final Verdict (Anomaly Detection)

Finally, we feed the distance matrix into an **Isolation Forest**.

- If the text fits the author's pattern, it is classified as "Normal" (Cluster 1).
- If the text deviates (even slightly), it is flagged as an "Anomaly" (Cluster 2 - Impostor). We use **K-Medoids** to perform this final clustering cleanly.

7. Success Metrics

How will we know if we succeeded? We will measure the project using quantitative scientific metrics:

- **Accuracy:** The percentage of correct identifications.
- **F1-Score:** The most important metric for us, as it balances Precision and Recall (crucial when dealing with imbalanced data like impostors).
- **Robustness Score:** We will run specific "Stress Tests" with adversarial data to see if the model breaks.

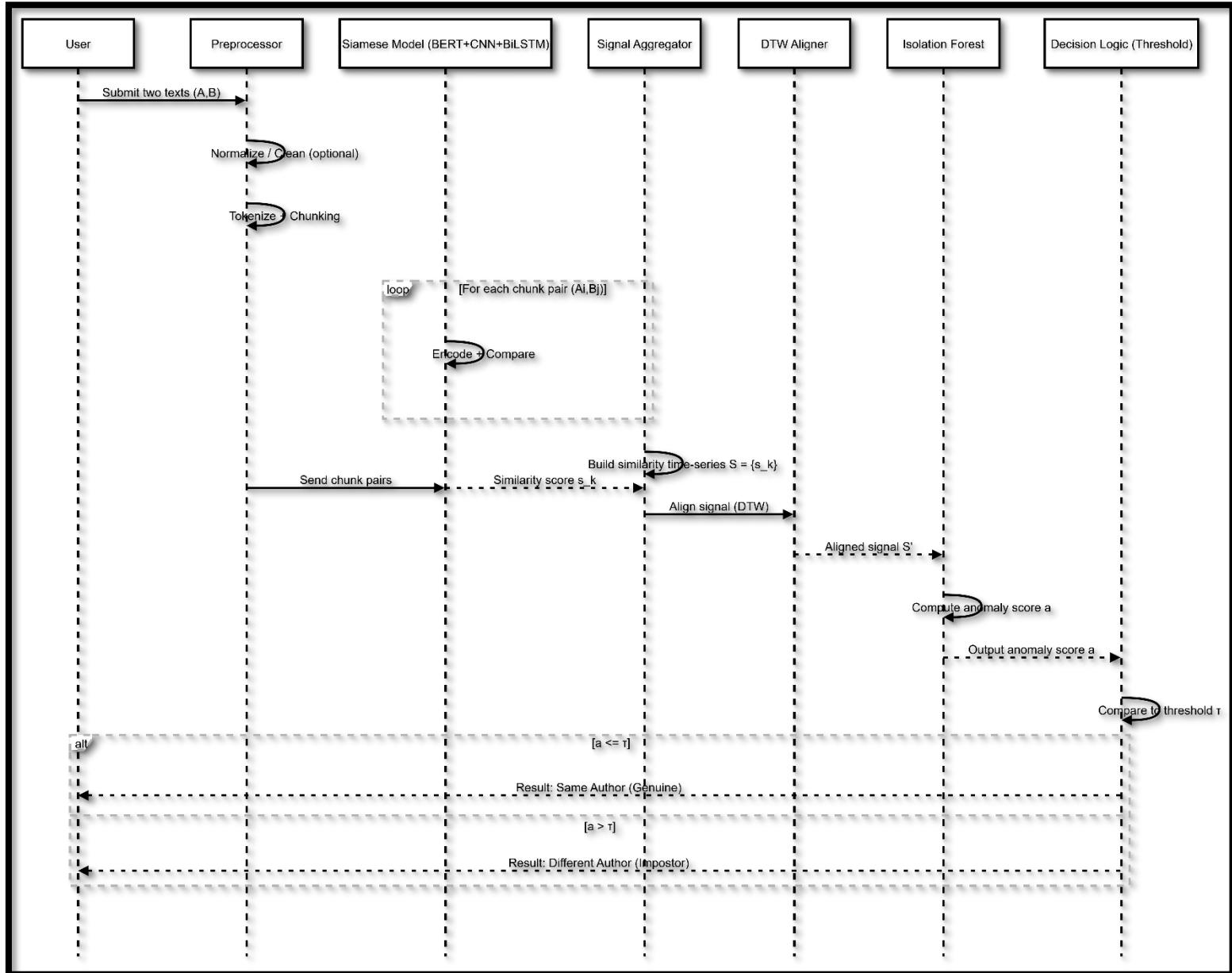
8. Testing Plan

In Phase B, we will validate the research through a rigorous testing process:

- **Unit Tests:** Checking individual components (e.g., "Does the Tokenizer split words correctly?", "Does the Siamese Network share weights?").

- **Integration Tests:** Checking the full flow. For example, feeding a text into the input and verifying that the Signal Aggregation module produces a valid vector.
- **Adversarial Testing:** We will intentionally attack our model with "Mimicry" examples to verify that the **Impostor Projection** logic is working and correctly flagging them as fakes.

Sequence Diagram - Inference Phase



Testing & Evaluation

The following test plan outlines the verification procedures for the system's components, ensuring data integrity, model convergence, and accurate anomaly detection.

5.1 Data Preparation & Validation Tests

Test ID	Component	Test Description	Expected Result
TP-01	Tokenizer	Validate BERT Tokenizer handles special characters and sub-word splitting correctly.	Tokenizer splits words accurately without crashing on special symbols.
TP-02	Chunking Logic	Verify documents split into chunks of exactly 512 tokens or less.	No data loss; all chunks are ≤ 512 tokens.
TP-03	Dataset Integrity	Scan dataset for corrupt entries, empty strings, or mismatched labels.	Script identifies and removes/flags all invalid entries.

5.2 Model Training Tests

Test ID	Component	Test Description	Expected Result
TR-01	Convergence	Monitor Binary Cross-Entropy (BCE) Loss over epochs.	Loss curve decreases steadily; no spikes or oscillation.
TR-02	Gradient Flow	Verify gradients propagate through BERT, CNN, and BiLSTM layers.	Non-zero gradients observed in all layers (no vanishing gradients).
TR-03	Overfitting	Compare Training Loss vs. Validation Loss to trigger Early Stopping.	Training stops automatically when validation loss increases.

5.3 Integration & System Tests

Test ID	Component	Test Description	Expected Result
SYS-01	Signal Aggregation	Verify chunk-level scores are averaged into a structured time-series signal.	Valid vector signal produced for each text batch.
SYS-02	DTW Alignment	Input pairs of signals with different lengths to DTW module.	Valid Distance Matrix produced; alignment handles length differences.
SYS-03	Anomaly Detection	Inject known random noise signals into Isolation Forest.	Algorithm flags outliers with a high anomaly score.



6: Conclusion & Future Work

6.1. Summary of Phase A Achievements

This research phase (Phase A) was dedicated to the comprehensive theoretical analysis and architectural design of an Authorship Verification system capable of operating in adversarial environments. The primary achievement of this phase is the definition of a novel, hybrid algorithmic framework that addresses significant gaps identified in traditional stylometry—specifically the inability to handle short texts and intentional mimicry attacks.

Key accomplishments in Phase A include:

- **Problem Definition:** We distinguished the task of "Verification" from standard "Attribution," highlighting the difficulty of the Open-Set problem where the impostor is unknown.
- **Architectural Design:** We designed a Siamese Network architecture that integrates BERT for semantic context with a CNN-BiLSTM hybrid layer to capture local stylistic patterns and sequential writing rhythms.
- **Methodological Innovation:** To tackle data sparsity and adversarial challenges, we incorporated the Impostor Projection Method (Seidman, 2013) into the training loop and adapted Dynamic Time Warping (DTW) to treat text as a temporal signal rather than a static bag-of-words.
- **Anomaly Detection Strategy:** We formulated the final decision logic using an Isolation Forest algorithm to provide a robust anomaly score, reducing reliance on fixed thresholds.

6.2. Plan for Phase B: Implementation & Validation

Phase B will focus on converting the theoretical blueprint designed in Phase A into a fully functional software prototype. The objective is to provide empirical evidence that the proposed architecture outperforms baseline methods.

The implementation roadmap includes:

1. **Core Development:** Writing the complete codebase in Python using the PyTorch framework, integrating the HuggingFace Transformers library for BERT embeddings.
2. **Training & Optimization:** The model will be trained on authentic authorship datasets. We will employ the AdamW optimizer and implement Early Stopping mechanisms to prevent overfitting, a critical risk when dealing with deep neural networks on limited text samples.
3. **Adversarial Stress Testing:** A key component of Phase B is the validation of the system's robustness. We will conduct "Stress Tests" by injecting high-quality imitation attacks (generated by both humans and AI) to verify the efficacy of the Impostor Projection method.
4. **Performance Evaluation:** The system will be evaluated using quantitative metrics, specifically Accuracy and F1-Score, to ensure a balance between Precision and Recall in distinguishing genuine authors from impostors.

7: References

Academic References

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Appendix A: Generative AI Disclosure

A.1. Overview of AI Usage

Throughout the research and documentation phases of this project, several Generative AI tools were utilized to assist with brainstorming, structural planning, language refinement, and visual asset generation. The core research logic, algorithm selection, and architectural decisions remain the sole intellectual property of the author.

A.2. Detailed Usage Log

Tool Name	Purpose	Link	Example Prompts / Usage Description
ChatGPT (OpenAI)	Text refinement & Brainstorming	https://chat.openai.com	<p><i>"Refine the following paragraph to sound more academic and formal: [Draft Text]..."</i></p> <p><i>"Suggest a logical structure for a chapter describing a Siamese Network architecture."</i></p>
Gemini (Google)	Content structuring & editing	https://gemini.google.com	<p><i>"Help me organize the 'Future Work' section based on my project's limitations."</i></p> <p><i>"Check my references list for APA formatting consistency."</i></p>
Draw.io (Diagrams.net)	Diagram Creation	https://app.diagrams.net	Used to design the system architecture and training flowcharts. (Note: AI features within the tool were not used; the tool was used as a canvas).
Artlist.io / Stock AI	Visual Assets	https://artlist.io	Generation of illustrative icons and conceptual images (e.g., "Authorship Verification concept art", "Cybersecurity lock and key 3D icon").

A.3. Verification Statement

I hereby declare that all AI-generated content was reviewed, verified, and edited by me to ensure accuracy and alignment with the project's goals. No AI tool was used to generate false data or fabricate experimental results.