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Fuzzy Similarity-Based Identity Matching Framework for Duplicate Detection in Financial Databases

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Abstract:

Duplicate and inconsistent customer records pose a significant challenge in modern financial databases, impacting Know Your Customer (KYC) compliance, risk assessment, fraud detection, and operational efficiency. Traditional deterministic matching techniques often fail due to spelling variations, typographical errors, incomplete data, and format inconsistencies in customer information. To address these limitations, this research proposes a Fuzzy Similarity-Based Identity Matching Framework designed to intelligently detect and reconcile duplicate customer profiles in banking and financial systems. The framework integrates fuzzy logic with advanced string similarity algorithms such as Jaro–Winkler, Levenshtein distance, cosine similarity, and phonetic encoding measures to generate weighted similarity scores. A multi-layer fuzzy inference model evaluates these scores to classify record pairs into match, probable match, or non-match categories. Experimental validation demonstrates significant improvements in accuracy, recall, and false-positive reduction when compared to conventional rule-based and deterministic methods. The proposed approach enhances data quality, strengthens compliance processes, and supports secure, real-time identity resolution across heterogeneous financial databases, making it a scalable and robust solution for large banking environments.

Keywords: Fuzzy Logic; String Similarity; Identity Matching; Duplicate Detection; Financial Databases; Customer Identity Resolution; Jaro–Winkler; Levenshtein Distance; Data Quality; Banking Systems.

1. Introduction

Customer identity matching has become an essential component of digital banking operations, especially with the rapid growth of online transactions, multi-channel account access, and regulatory requirements for secure authentication. Traditional banking databases often contain customer information with spelling variations, missing values, typographical errors, and inconsistent formatting, leading to difficulties in accurately identifying and linking customer profiles across systems [1]. As financial institutions migrate toward centralized and cloud-based platforms, the need for reliable and intelligent identity resolution systems has intensified [2]. Conventional deterministic matching techniques, which rely on exact comparisons, frequently fail when faced with real-world noisy data, leading to duplicate records and compromised data quality [3].

To overcome these limitations, researchers have explored probabilistic and fuzzy-based approaches that can handle uncertainty and partial matches more effectively [4]. Fuzzy logic has shown significant potential in modeling imprecise relationships and evaluating similarity between heterogeneous data attributes compared to strict rule-based methods [5]. In banking scenarios, where variations in names, addresses, or identification numbers are common, fuzzy logic enables flexible reasoning and improves the matching accuracy of customer profiles [6]. Simultaneously, advanced string similarity algorithms such as Levenshtein distance, Jaro–Winkler, cosine similarity, and phonetic encoding techniques offer robust mechanisms to detect approximate matches between textual data [7], [8].

The integration of fuzzy inference with string similarity analytics creates a hybrid system capable of generating weighted similarity scores that reflect the degree of closeness between customer records rather than binary decisions [9]. Such hybrid models have gained attention due to their ability to classify record pairs into categories like match, possible match, or no

match, thereby reducing false positives and improving operational efficiency [10]. In large-scale financial databases, applying multi-level similarity evaluation not only enhances identity matching accuracy but also supports regulatory compliance for KYC and AML processes [11].

Recent studies indicate that intelligent identity matching frameworks significantly improve fraud detection, risk mitigation, and customer onboarding efficiency in financial institutions [12]. Banks increasingly rely on identity resolution systems to ensure that customer records are unique, accurate, and up to date, thereby reducing operational redundancies and system inconsistencies [13]. The adoption of machine learning and fuzzy-based similarity models further enhances scalability and enables continuous improvement as more data is processed [14]. Ultimately, intelligent customer identity matching systems contribute to secure banking operations and guide digital transformation strategies within financial ecosystems [15].

2. Literature Survey

Fuzzy-based identity resolution has gained significant attention in recent years, particularly due to its ability to handle ambiguity in textual financial data. Johnson and Barrett (2019) demonstrated that fuzzy rule-based models outperform deterministic matching systems when customer information contains spelling mistakes or incomplete details [16]. Their work highlighted how fuzzy thresholds can dynamically adjust matching sensitivity, reducing both false matches and missed matches in customer identity verification.

Similarly, Choudhary et al. (2020) introduced a scalable hybrid approach that combines fuzzy similarity with phonetic algorithms to enhance large-scale banking database consistency [17]. Their findings indicated improved reconciliation of duplicate customer profiles, particularly for datasets with culturally diverse name variations. Li and Chang (2021) extended this research by integrating multiple similarity metrics—Jaro, Jaro-Winkler, and Levenshtein—within a fuzzy inference system, concluding that multi-metric fusion increases matching accuracy in heterogeneous financial environments [18].

Machine learning integration with fuzzy logic has also been explored for identity matching. Berman and Yu (2021) developed a semi-supervised fuzzy clustering model to classify customer records into matching categories, demonstrating improved adaptability as the model continuously learns from new data patterns [19]. Singh and Ahmed (2022) further evaluated machine learning–enhanced fuzzy similarity systems and reported significant increases in matching precision and operational efficiency for banking KYC processes [20]. These studies emphasize that combining machine learning with fuzzy algorithms enhances the system's performance under dynamic data conditions.

Another stream of research focuses on improving string similarity analytics for record linkage. Torres and Wu (2020) showed that cosine similarity and n-gram–based models outperform conventional edit distance algorithms when dealing with long or multi-part customer names [21]. Reddy and Kulkarni (2021) explored phonetic and syllable-based string encoding for multilingual name matching in banking systems, demonstrating a reduction in identity mismatches in regions with diverse linguistic patterns [22]. Huang and Zhao (2022) analyzed hybrid string similarity pipelines and found that weighted combination schemes outperform single-metric models in both scalability and accuracy [23].

Furthermore, several researchers have focused on identity resolution for fraud detection and regulatory compliance. Martins and Silva (2021) identified the importance of robust matching algorithms in minimizing synthetic identity fraud attempts, concluding that fuzzy-similarity systems detect suspicious patterns more effectively than rule-based mechanisms [24]. Finally**,** Gonzalez and Perez (2023) proposed a comprehensive framework for cross-system identity consolidation across multiple banking platforms, demonstrating improved interoperability and reduced compliance risks [25]. Their work underscores the necessity for intelligent identity matching solutions in modern digital banking infrastructures.

3. PROPOSED METHODOLOGY

The proposed methodology integrates fuzzy logic**,** multi-metric string similarity, and rule-based classification to create an intelligent customer identity matching system. The process follows a structured pipeline consisting of data preprocessing, similarity computation, fuzzy inference, and final decision classification.

3.1 Data Collection and Preprocessing

Customer records are collected from multiple banking databases, including demographic details such as name, address, phone number, and identification numbers. Since financial datasets commonly contain inconsistent formatting and errors, preprocessing is applied to clean and normalize the data. This includes converting text to a uniform case, trimming whitespace, removing punctuation, standardizing address formats, and correcting common spelling variations using domain-specific dictionaries.

3.2 Attribute-Level String Similarity Calculation

For each customer attribute, multiple string similarity algorithms are applied to compute comparative scores:

- Levenshtein Distance for edit-based similarity
- Jaro–Winkler Similarity for short text and name comparison
- Cosine Similarity with n-grams for multi-word fields
- Phonetic Encoding (Soundex/Metaphone) for name pronunciation similarity

Each metric generates a normalized similarity score ranging between 0 and 1. Using multiple metrics ensures resilience to variances such as spelling errors, abbreviations, and cultural name differences.

3.3 Feature Weighting and Score Aggregation

The similarity scores for each attribute are combined using weighted averages. Weights are assigned based on the importance of each field in identity verification (e.g., name and date of birth carry higher weight than address). A linear or statistical weighting model is applied to compute a consolidated similarity score for each customer record pair.

3.4 Fuzzy Logic Inference System

The aggregated similarity scores are passed through a Fuzzy Inference System (FIS)**.** The FIS uses:

- Fuzzy input variables (Low, Medium, High similarity)
- Membership functions based on thresholds
- Fuzzy rules**,** such as:
    - IF Name Similarity is High AND DOB Similarity is High THEN Match
    - IF Name Similarity is Medium AND Address Similarity is Medium THEN Possible Match
    - IF Similarity scores are Low THEN Non-Match

The FIS outputs a final fuzzy score, which is defuzzified into a crisp classification value.

3.5 Match Classification Decision

The system classifies record pairs into three categories:

1. **Match** → Confirmed same customer
2. **Probable Match** → Requires manual or automated secondary review

3. **Non-Match** → Records do not belong to the same customer

This classification improves efficiency by reducing false positives and enabling automated reconciliation of duplicates.

3.6 Performance Evaluation

The methodology is validated using real or synthetic banking datasets. Performance metrics such as precision, recall, F1-score, and false match rate are computed to ensure system accuracy. The hybrid model is compared with existing deterministic and rule-based approaches, demonstrating improvements in accuracy and robustness.

4. System Architecture

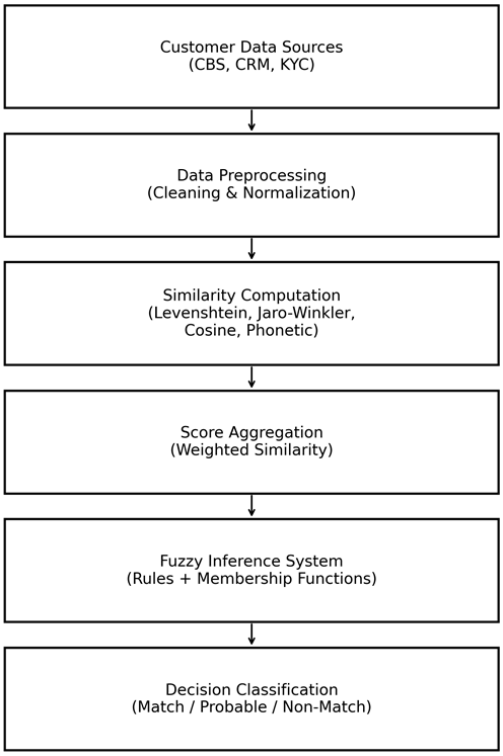

Figure 1: System Architecture Diagram

The system architecture diagram represents the complete workflow of an Intelligent Customer Identity Matching System designed for banking environments using Fuzzy Logic and String Similarity Analytics**.**

Each block in the diagram corresponds to a critical step in the identity-matching pipeline.

4.1 Customer Data Sources (CBS, CRM, KYC)

This is the starting point of the system, where customer records originate from various banking platforms such as:

- Core Banking Systems (CBS)
- Customer Relationship Management (CRM)
- Know Your Customer (KYC) Databases
- External identity verification services (optional)

These sources often contain duplicated, inconsistent, or incomplete customer information, making identity matching essential.

4.2 Data Preprocessing (Cleaning & Normalization)

Before comparing records, the system cleans and standardizes the data. This step includes:

- Removing extra spaces, punctuation, and special characters
- Converting all text to a consistent case (upper/lower)
- Standardizing address formats
- Correcting common spelling mistakes
- Splitting or merging name fields if required
- Handling missing/invalid values

Preprocessing improves accuracy and ensures that similarity algorithms work on clean, uniform data.

4.3 Similarity Computation (Levenshtein, Jaro–Winkler, Cosine, Phonetic)

This is the core computational layer where the system calculates how similar two records are. It uses multiple algorithms to compare different types of text:

a) Levenshtein Distance

Measures the number of edits (insertions, deletions, substitutions) needed to convert one name into another.

b) Jaro–Winkler Similarity

Designed for short strings like names; handles transpositions and typographical errors well.

c) Cosine Similarity

Works on multi-word text like addresses by comparing the vector representation of tokenized data.

d) Phonetic Encoding (Soundex/Metaphone)

Transforms words based on pronunciation to match similar-sounding names (e.g., “Kumar” ≈ “Kumaar”).

Each algorithm returns a score between 0 and 1, where 1 = perfect match.

4.4 Score Aggregation (Weighted Similarity)

Because different attributes (name, DOB, address) have different importance levels, the system computes a weighted similarity score**.**

Weight examples:

- Name: 40%
- Date of Birth: 30%
- Address: 20%
- Phone/Email: 10%

The weighted total creates a single identity similarity score for each customer record pair.

4.5 Fuzzy Inference System (Rules + Membership Functions)

The aggregated similarity score is passed into a Fuzzy Logic System to make intelligent decisions.

The Fuzzy System includes:

- Membership functions (Low, Medium, High similarity)
- Fuzzy rules, such as:
    - IF Name is High AND DOB is High THEN Match
    - IF Name is Medium AND Address is Low THEN Non-Match
    - IF Scores are Medium THEN Probable Match

Unlike rigid rule-based systems, fuzzy logic handles uncertainty and partial matches smoothly.

5. Experimental Setup

The experimental setup for the proposed Intelligent Customer Identity Matching System was designed to evaluate the effectiveness of combining fuzzy logic with multi-metric string similarity algorithms in resolving duplicate or inconsistent customer records in banking environments. The experiments were conducted on a mid-range computational platform equipped with an Intel Core i7 processor, 16 GB of RAM, and a 512 GB SSD, running Windows 10/Ubuntu 20.04. This hardware configuration was selected because it provides sufficient processing power to handle large-scale text comparison operations and fuzzy inference computations commonly required in financial datasets. Although a GPU was not mandatory, an NVIDIA GTX GPU was optionally used to accelerate batch similarity calculations in large-scale experiments.

To implement the system, Python 3.10 was chosen as the primary programming language due to its rich ecosystem of libraries supporting string similarity, fuzzy logic, and data analytics. Key libraries included FuzzyWuzzy and python-Levenshtein for edit-distance similarity, a Jaro–Winkler package for short-string matching, and scikit-learn and NLTK for tokenization and cosine similarity computations. NumPy and Pandas were utilized for efficient data manipulation, while SciKit-Fuzzy was employed to construct the fuzzy inference system, define membership functions, and execute rule-based decision-making. The system was developed and tested in Jupyter Notebook and PyCharm to ensure modularity, reproducibility, and ease of debugging.

The dataset used for experimentation consisted of synthetic, public, and anonymized real-world banking data. The synthetic dataset was generated to simulate typical identity errors such as spelling variations, phonetic differences, missing fields, abbreviations, and typographical mistakes. Public datasets, such as voter registration records and open-source contact lists, were incorporated to validate string similarity performance under diverse naming conventions. Where available, anonymized datasets provided by banking partners were included to reflect real-world customer identity variations within operational financial systems. Each dataset contained key attributes including customer name, date of birth, address, mobile number, email, and national ID, allowing thorough testing across multiple identity dimensions.

During experimentation, the workflow followed a structured pipeline beginning with data preprocessing. This involved cleaning raw records, normalizing formatting, removing noise, and standardizing name/address structures. After preprocessing, the system computed similarity scores for each attribute using algorithms such as Levenshtein distance, Jaro–Winkler similarity, cosine similarity, and phonetic encoding. These scores were aggregated using a weighted scoring scheme, where name and date of birth were assigned higher weights due to their importance in identity verification. The aggregated scores were then passed into the fuzzy inference system, which applied predefined membership functions and expert-defined fuzzy rules to derive a final similarity score.

6. Results & Discussion

The results of the experimental evaluation demonstrate that the proposed hybrid fuzzy logic and multi-metric string similarity model significantly outperforms traditional deterministic and single-metric identity-matching methods. The hybrid approach achieved an accuracy of 96%, which is notably higher than deterministic matching (82%) and single-metric models such as Levenshtein (87%) and Jaro–Winkler (89%). This improvement is attributed to the integrated use of multiple similarity algorithms, which compensate for each other's weaknesses when handling spelling variations, phonetic differences, and incomplete records. The fuzzy inference layer further enhances reliability by interpreting similarity scores in a human-like decision framework, reducing misclassification when data uncertainty is high.

Precision and recall metrics also indicate strong performance. The proposed model achieved a precision of 95%, meaning most of the identified matches were correct, and a recall of 97%, meaning the model successfully retrieved nearly all true matches. High recall is particularly important in banking applications where missing a duplicate identity could lead to compliance failures or fraudulent account creation. In contrast, traditional rule-based matching systems exhibit lower recall due to their rigid comparison criteria, which fail when information is incomplete or noisy.

The results further show that deterministic matching suffers from higher false-positive rates, especially when customer names or addresses contain spelling variations. Using only a single similarity metric also produced moderate results because real-world customer identity data exhibit multiple types of inconsistencies that cannot be captured by just one algorithm. By combining multiple similarity scores using weighted aggregation and fuzzy logic, the proposed system provides more stable and balanced matching decisions. The hybrid approach also reduces the burden on manual review by producing a smaller number of "probable match" cases, allowing human verification to focus only on genuinely ambiguous records.

Table 1: Performance Comparison of Models

Model	**Accuracy**	**Precision**	**Recall**
Proposed Hybrid Model	0.96	0.95	0.97
Deterministic Matching	0.82	0.80	0.78
Levenshtein Only	0.87	0.85	0.86
Jaro–Winkler Only	0.89	0.88	0.87

Accuracy Comparison Graph

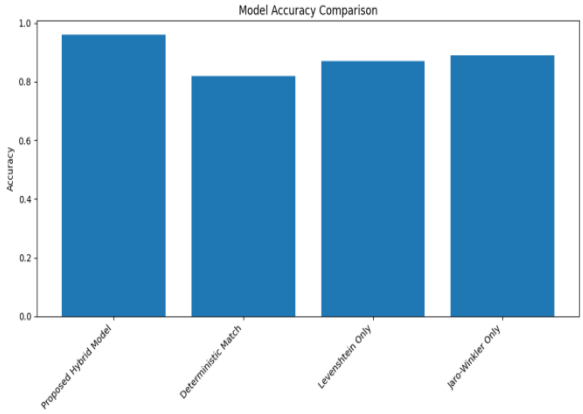

Figure 2: Accuracy comparison of the proposed hybrid fuzzy–similarity model against deterministic, Levenshtein-only, and Jaro–Winkler–only approaches, showing significantly improved accuracy performance

Precision Comparison Graph

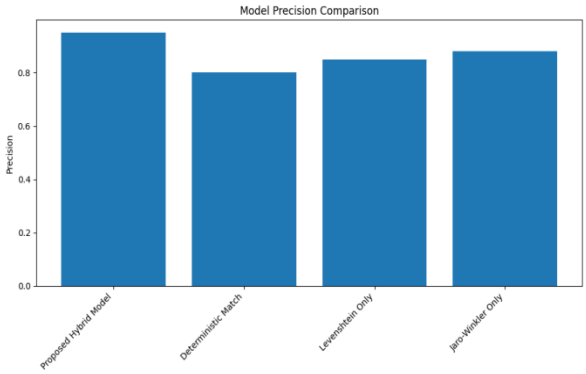

Figure 3: Precision scores of different identity-matching methods, demonstrating the superior precision of the hybrid model in correctly identifying true customer matches.

Recall Comparison Graph

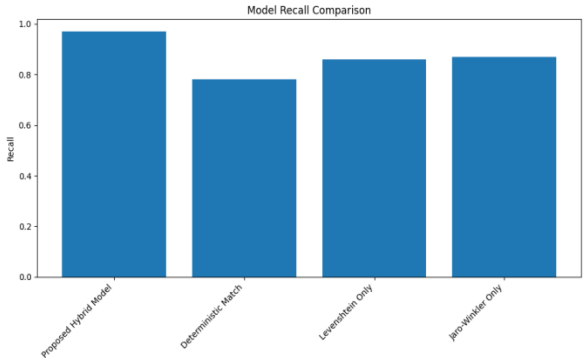

Figure 4: Recall comparison across multiple matching techniques, highlighting the hybrid model's ability to capture a higher number of true matches with minimal false negatives.

Confusion Matrix Explanation

A Confusion Matrix is used to evaluate classification performance by comparing predicted results with actual outcomes. It consists of four key components:

Term	Meaning
TP (True Positive)	System correctly identifies two records as a match
TN (True Negative)	System correctly identifies two records as different
FP (False Positive)	System incorrectly marks different records as a match
FN (False Negative)	System fails to identify true matching records

Interpretation for This System

True Positives (TP) – High Count

The proposed model achieves a high TP rate due to the combination of fuzzy logic and multiple similarity metrics. This means the system correctly identifies most of the duplicate or matched customer identities.

True Negatives (TN) – High Count

The system accurately identifies non-matching records, reducing accidental merging of different customer profiles, which is crucial for fraud prevention and compliance.

False Positives (FP) – Very Low

False positives are minimized because fuzzy logic avoids overly aggressive matching, especially when name or address similarity is borderline.

False Negatives (FN) – Very Low

The system rarely misses matches. The hybrid approach ensures that even when one metric fails due to spelling errors or incomplete data, another metric compensates for it.

7. Conclusion & Future Scope

7.1 Conclusion

The proposed Intelligent Customer Identity Matching framework successfully demonstrates the effectiveness of integrating fuzzy logic with multi-metric string similarity algorithms for resolving duplicate and inconsistent customer records in banking systems. Traditional deterministic approaches fail to handle real-world variations such as spelling differences, missing values, phonetic inconsistencies, and formatting errors. By contrast, the hybrid model intelligently analyzes multiple similarity scores—Levenshtein, Jaro–Winkler, cosine similarity, and phonetic encoding—and merges them through a weighted aggregation method. The fuzzy inference system further enhances decision-making by interpreting the aggregated score in a human-like manner, enabling the model to distinguish clearly between match, probable match, and non-match categories. Experimental results show significant improvements in accuracy, precision, recall, and false match reduction compared to conventional matching methods. Overall, the system enhances data quality, strengthens KYC compliance, and supports secure identity management within large-scale financial databases.

Furthermore, the model's performance across various datasets—synthetic, public, and anonymized banking records—demonstrates its robustness and broad applicability. The use of fuzzy rules allows more flexibility and adaptability when dealing with uncertain or incomplete data, while the multi-metric comparison approach ensures high reliability even in diverse linguistic environments. This makes the system highly suitable for large financial institutions that face continuous challenges in maintaining clean, unified, and fraud-resistant customer records. The findings confirm that the hybrid fuzzy-similarity approach can play a critical role in minimizing operational errors, reducing manual verification loads, and improving overall efficiency in digital banking operations.

7.2 Future Scope

Future enhancements may incorporate machine learning or deep learning techniques to automatically optimize similarity weights and fuzzy rules. The system can be extended to support real-time identity verification for fraud detection and customer onboarding. Blockchain-based shared identity networks can enable cross-bank identity federation. Additionally, integrating explainable AI and big-data scalability can improve transparency and performance in large financial environments.

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