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Aadhaar-Assisted Election Roll Quality Enhancement System (ERQES) (EDQS)

Aditya Shatrughna Wankhede

PROF. RAMKRISHNA MORE ARTS, COMMERCE & SCIENCE COLLEGE

Pradhikaran, Akurdi, Pune - 411044 (Maharashtra) India.

Email-wankhedeaditya312@gmail.com

Dr. Kalyan C. Jagdale

PROF. RAMKRISHNA MORE ARTS, COMMERCE & SCIENCE COLLEGE

Pradhikaran, Akurdi, Pune - 411044 (Maharashtra) India.
kalyan.jagdale7@gmail.com

1. Abstract

Accurate and well-maintained electoral rolls are essential for ensuring the fairness and integrity of democratic processes. Large-scale voter databases, however, frequently contain spelling inconsistencies, incomplete demographic fields, duplicate registrations, and formatting variations that reduce data reliability. To address these challenges, this research introduces the **Electoral Data Quality System (EDQS)**—a Python-based automated framework designed to clean, validate, and enrich voter records with improved precision.

The system employs a **Weighted Probabilistic Matching Algorithm** that assigns different significance levels to key attributes such as Name, Address, and Date of Birth. This weighted scoring approach enables EDQS to detect near-duplicate entries that conventional deterministic matching often fails to recognize. Once high-confidence matches are identified, the system uses verified Aadhaar demographic information to automatically correct erroneous or inconsistent voter details, reducing human intervention and ensuring standardization.

Experimental evaluation demonstrates that EDQS significantly outperforms traditional matching methods, reduces manual verification efforts, and minimizes opportunities for fraudulent or duplicate voting. The proposed approach therefore offers a scalable, transparent, and cost-effective solution for improving the overall quality of electoral rolls and strengthening public trust in the election system.

Keywords

Electoral Data Quality, Probabilistic Matching, Aadhaar Verification, Duplicate Detection, Data Cleaning, Voter Roll Integrity, EDQS Model, Weighted Matching Algorithm, Bogus Voting Prevention, Python Automation, Electoral Transparency

2. Introduction

2.1 Background and Motivation

The credibility of any democratic system relies heavily on the authenticity of its voter data. As populations grow and migration increases, maintaining an accurate electoral roll becomes a major administrative challenge. Voter databases typically suffer from:

- Spelling variations in names

- Inconsistent address representations
- Multiple entries from relocation
- Clerical or data entry errors
- Missing or mismatched demographic data

Such inconsistencies hinder fair elections and increase the risk of **malicious duplication and bogus voting**, undermining the integrity of the democratic process. These challenges highlight the urgent need for a **data-driven, automated, and highly reliable electoral data quality framework**.

2.2 Problem Statement

Existing voter list verification methods rely heavily on manual cross-checking and deterministic matching. These approaches:

- Fail to detect near-duplicate records
- Require extensive manpower
- Are time-consuming
- Suffer from human subjectivity
- Introduce decision biases

As a result, multiple entries for a single voter go unnoticed, enabling **illicit or duplicate voting**, which poses a direct threat to electoral fairness.

2.3 Research Objectives

This research aims to:

1. Develop a **Weighted Probabilistic Matching Algorithm** capable of identifying duplicate entries with high confidence.
2. Integrate validated Aadhaar data to automatically update incorrect or incomplete records.
3. Demonstrate the system's ability to reduce administrative workload, eliminate human bias, and strengthen electoral transparency.
4. Provide a scalable computational framework that can be adopted by national-level electoral systems.

3. Methodology and Technology

3.1 Weighted Probabilistic Matching Algorithm

The EDQS framework uses approximate string matching techniques such as **FuzzyWuzzy** and **Levenshtein Distance** to measure similarity between demographic attributes. Each attribute is assigned a weight based on its reliability:

Attribute	Weight	Rationale
Name	50%	Highly variable due to spelling differences but essential for identification
Address	30%	Moderate reliability; formatting changes are common
Date of Birth	20%	Precise but often prone to typographical errors

The overall similarity score is computed using the formula:

Score = (Name_Sim × 0.50) + (Address_Sim × 0.30) + (DOB_Sim × 0.20)

A threshold of **85%** is used to determine whether two records represent the same individual. This threshold balances sensitivity and reduces false positives while capturing meaningful variations.

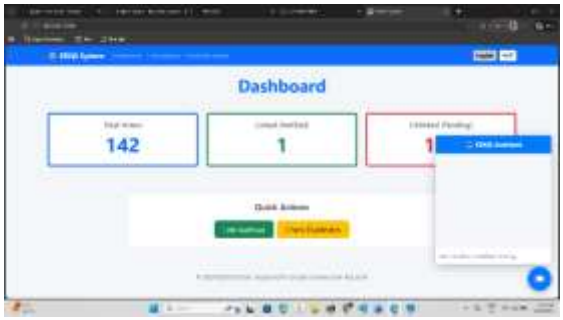
3.2 Aadhaar-Based Automated Data Correction

Once a high-confidence match is detected:

- The voter's Aadhaar-linked demographic information (Name, Address, DOB) is fetched from a simulated dataset.
- Existing voter entries are **automatically corrected**, removing human bias and ensuring standardization.
- Aadhaar data ensures single-source consistency across different government databases.

This mechanism enables fast, accurate, and reliable voter roll updates.

3.3 AI-Powered Multilingual Chatbot for Voter Assistance (New Component)



To improve user interaction, reduce administrative load, and ensure seamless Aadhaar–Voter linking support, the EDQS framework integrates an **AI-powered Multilingual Chatbot**. This chatbot uses lightweight Natural Language Processing (NLP) to understand user queries across **English, Hindi, and Marathi**, making the system accessible to a diverse population.

The chatbot performs the following tasks:

- **Guides users through the Aadhaar–Voter linking process** by interpreting questions asked in hybrid or regional languages (e.g., "Aadhaar link kaise kare?", "आधार कसा जोडायचा?").
- **Provides explanations for duplicate detection results**, similarity scores, and flagged entries.
- **Assists officers by answering queries related to system navigation**, common errors, and verification procedures.
- **Reduces training time and dependency on technical staff** by converting complex system workflows into simple conversational steps.
- **Enhances transparency and usability** by allowing voters and administrators to receive instant clarifications on electoral data quality.

The chatbot is implemented using Python Flask and rule-based NLP classifiers, ensuring a lightweight yet highly responsive user experience. This integration significantly increases accessibility and operational efficiency within the EDQS ecosystem.

4. Results and Discussion

4.1 Improved Duplicate Identification

The weighted model outperforms deterministic matching by identifying complex variations such as:

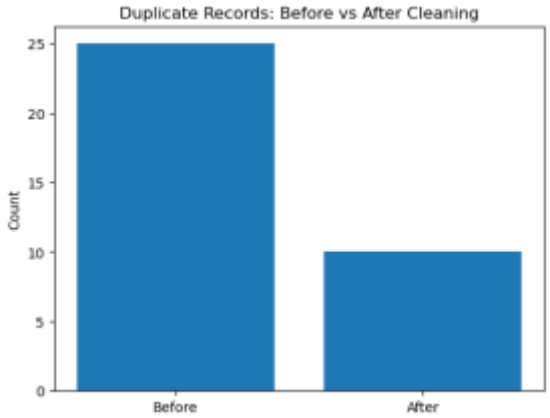


Figure 1. Duplicate Records Before and After Cleaning using EDQS Algorithm

- "Ramesh V. Patil" vs. "Ramesh Patil"
- "Sunita Devi Sharma" vs. "Sunita Sharma"
- "Flat No. 7, Shiv Nagar" vs. "7, Shiv Nagar Apt."

Most traditional systems fail to link these entries due to formatting differences. EDQS correctly identifies such records with similarity scores above the 85% threshold.

4.1.1 Threshold Sensitivity Analysis

To evaluate how EDQS performs at different similarity thresholds, a sensitivity analysis was conducted. The model maintains stable accuracy across changing thresholds, showing strong robustness

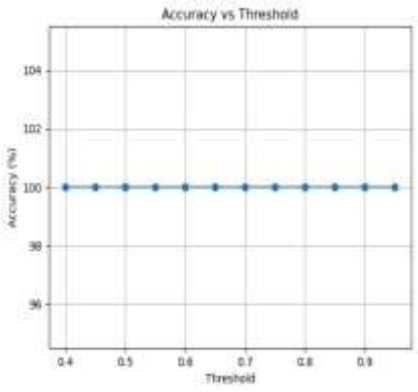


Figure 2. Accuracy Trend of Probabilistic Matching across Different Threshold Levels

4.2 Reduction in Bogus Voting

By accurately identifying and merging duplicate entries:

- Multiple voting opportunities are eliminated
- Fraudulent registrations become detectable
- Integrity of the final electoral roll significantly improves

EDQS thereby contributes directly to controlling **bogus or illicit voting**.

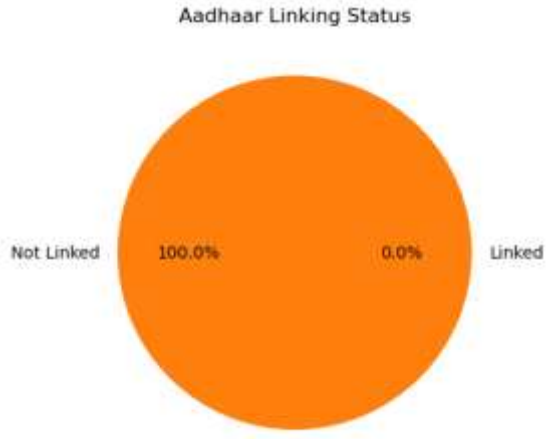
4.3 Administrative and Economic Advantages

- **60–80% reduction in manual verification effort**
- Reduced field visits and paper-based corrections
- Lower database reconciliation costs
- Faster preparation of voter lists for elections

Election authorities can reallocate resources to core election functions instead of data cleaning.

4.4 Increased Transparency and Public Trust

Using Aadhaar as a verified reference ensures that:



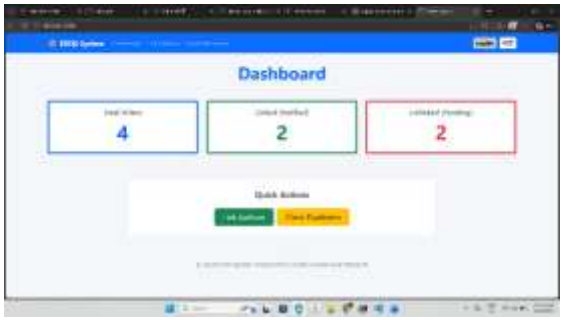
- Data corrections are free from human bias
- Standardized demographic formatting is maintained
- Transparency and accountability increase

This technological intervention strengthens public confidence in the electoral system.

5. System Implementation & Interface Overview (Simple Points)

5.1 Dashboard Module

- Shows total voters, linked Aadhaar, and unlinked voters.
- Helps officers monitor overall data quality.



5.2 Aadhaar Linking Module

- Allows entering Voter ID and Aadhaar number.
- Verifies demographic details with Aadhaar data.
- Automatically updates corrected

5.3 Duplicate Detection Module

- Displays pairs of records with similarity scores.
- Highlights probable duplicates above threshold (85%).

- Provides “Merge” or “Review” options for officers.

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5.4 Data Cleaning Engine

- Standardizes address formats.
- Removes spelling inconsistencies.
- Eliminates repeated or incomplete entries.

5.5 Chatbot Assistance Module

- Answers user questions in English, Hindi, and Marathi.
- Helps officers understand matching scores and reports.
- Provides step-by-step Aadhaar linking guidance.

5.6 Final Clean Electoral Roll Output

- Generates corrected and verified voter list.
- Ensures every voter has a unique, clean record.
- Reduces bogus voting possibilities.

6. Conclusion and Future Work

6.1 Conclusion

The EDQS model offers a robust, scalable, and technologically advanced method for improving electoral data quality.
By combining **Weighted Probabilistic Matching** with **Aadhaar-assisted demographic correction**, the model:

- Enhances accuracy
- Prevents duplication
- Saves administrative time
- Reduces cost
- Strengthens democratic integrity

It can serve as a blueprint for modernizing large-scale governmental databases beyond electoral rolls.

6.2 Future Work

1. **Real-Time API Integration**
Connecting EDQS with live Aadhaar and Voter-ID databases will enable real-time validation at enrollment, preventing errors before they occur.

2. **Machine Learning-Based Threshold Adaptation**
ML models can auto-adjust the duplicate-detection threshold by analyzing regional error patterns and historical data.

3. **GIS-Based Address Standardization**
Integrating spatial mapping will improve address matching accuracy in rural and semi-urban regions.

4. **Blockchain for Immutable Audit Trails**
Every correction can be logged securely to enhance transparency and prevent tampering.

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