ALEIS – Aadhaar Life-Event Intelligence System

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Abstract

India's Aadhaar ecosystem generates one of the world's largest anonymized citizen-interaction datasets through enrolments and updates. While traditionally used for administrative reporting, this data contains latent behavioral signals reflecting migration, demographic transitions, and socio-economic life events. This project introduces ALEIS (Aadhaar Life-Event Intelligence System) a modular analytics framework that interprets Aadhaar update behavior as a proxy for real-world life events. By combining time-series analysis, anomaly detection, and a novel Life-Event Probability Index (LEPI), ALEIS enables early detection of demographic shifts and supports proactive, data-driven policymaking.

1. Introduction

Large-scale digital identity systems are often evaluated through static metrics such as enrolment counts or update volumes. However, such metrics overlook the temporal dynamics and behavioral intent behind citizen interactions. Aadhaar updates such as changes in address, mobile number, or biometric re-capture are frequently triggered by significant life events including relocation, employment change, marriage, aging, or family restructuring.

The absence of automated intelligence over these behavioral signals results in:

- Delayed recognition of migration trends
- Reactive policy decisions
- Inefficient allocation of administrative and social resources

ALEIS is designed to bridge this gap by transforming Aadhaar update data into a continuous demographic intelligence system.

2. Problem Statement

Despite the availability of large-scale Aadhaar enrolment and update data, current analysis remains limited to static aggregate reporting, failing to:

- Capture underlying life-event-driven behavior
- Detect sudden demographic or regional shifts
- Provide early warning signals for policymakers

This project addresses the need for a dynamic, interpretable, and scalable analytics pipeline that converts Aadhaar update activity into actionable societal insights.

3. Proposed Solution: ALEIS

The Aadhaar Life-Event Intelligence System (ALEIS) treats Aadhaar update behavior as a behavioral proxy for life events, moving beyond surface-level statistics.

Core Objectives

- Identify behavioral archetypes based on update frequency and timing
- Detect temporal and regional anomalies
- Quantify life-event intensity using a composite index (LEPI)
- Enable early policy intervention through automated insights

ALEIS is implemented as a modular Python-based pipeline, ensuring reproducibility, extensibility, and transparency.

4. Datasets Used

4.1 Data Source

- **UIDAI Aadhaar Enrolment and Update Dataset**
  - Fully anonymized
  - Aggregated at state and district levels
  - Provided specifically for analytical use

No personally identifiable information (PII) is used, ensuring strict privacy compliance.

4.2 Dataset Files and Attributes

Dataset File	**Description**	**Key Metric**
enrolment.csv	New Aadhaar registrations	enrolments
demographic.csv	Demographic information updates	total_updates
biometric.csv	Biometric re-capture updates	biometric_updates

Common Fields

- State
- District
- Date (processed into Year and Month)

5. Methodology

ALEIS follows a structured, multi-stage analytical workflow.

5.1 Data Cleaning and Preprocessing

Field Standardization

- Column names normalized to lowercase
- Whitespace removed for schema consistency

Deduplication

- Exact duplicate rows removed to maintain data integrity

Date Processing

- Date fields parsed into datetime format
- Temporal features extracted:
  - Year
  - Month

This enables robust time-series analysis.

5.2 Data Transformation and Integration

Monthly Aggregation

Data is aggregated at:

- State
- District
- Year
- Month

Aggregation uses sum-based metrics to preserve total activity.

Dataset Consolidation

- Outer joins merge enrolment, demographic, and biometric datasets
- Missing values filled with zero to represent inactivity

Validation Checks

- Negative value detection
- District coverage verification
- Schema consistency checks

5.3 Feature Engineering

Enrolment Velocity

- Month-over-month change in enrolments
- Detects sudden population inflow or administrative drives

Life-Event Probability Index (LEPI)

LEPI is a composite indicator designed to quantify life-event intensity.

It incorporates:

- Update frequency
- Temporal concentration of updates

Conceptual Interpretation

- Low LEPI → routine or stable behavior
- High LEPI → concentrated updates likely triggered by life events

The index is configurable and adaptable to different analytical priorities.

6. Data Analysis and Results

6.1 Societal Signal Detection

- Address and mobile updates show strong correlation with **internal migration cycles**
- Seasonal spikes align with:

    - Employment-related movement
    - Urbanization patterns

6.2 Anomaly Detection

ALEIS automatically flags districts with:

- Sudden spikes in LEPI
- Unusual deviations from historical baselines

These anomalies may indicate:

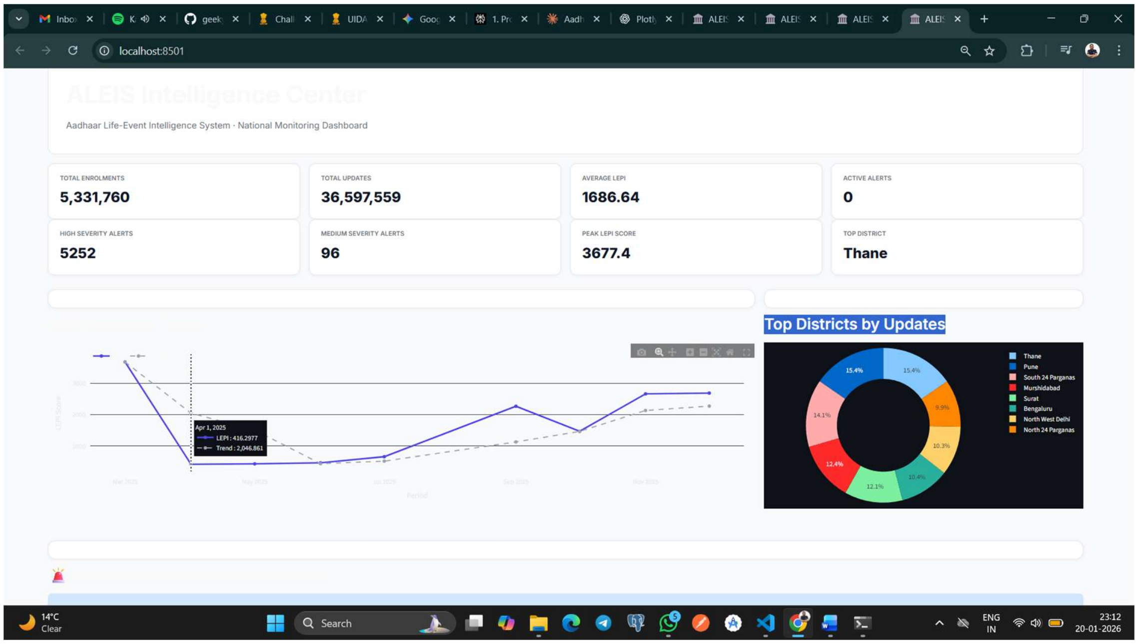
- Rapid migration
- Administrative overload
- Infrastructure or housing stress

6.3 Trend Analysis

- A 6-month rolling average is applied to smooth seasonal noise
- Long-term patterns reveal:
    - Gradual demographic transitions
    - Emerging urban or semi-urban growth corridors

7. Visualization and Outputs

ALEIS generates policy-ready analytical artifacts:



Automated Deliverables

- Markdown-based **Policy Briefs**
- Each report includes:
  - Detected anomalies
  - Trend summaries
  - Suggested intervention triggers

8. Impact and Applications

Policy Impact

- Early detection of migration and demographic shifts
- Proactive allocation of administrative resources
- Improved planning for housing, employment, and welfare schemes

Scalability

- Modular pipeline allows:
  - Integration of additional datasets

- Expansion to other citizen-service platforms

Ethical Design

- Fully anonymized data
- No individual-level inference
- Focus on macro-level societal intelligence

9. Conclusion

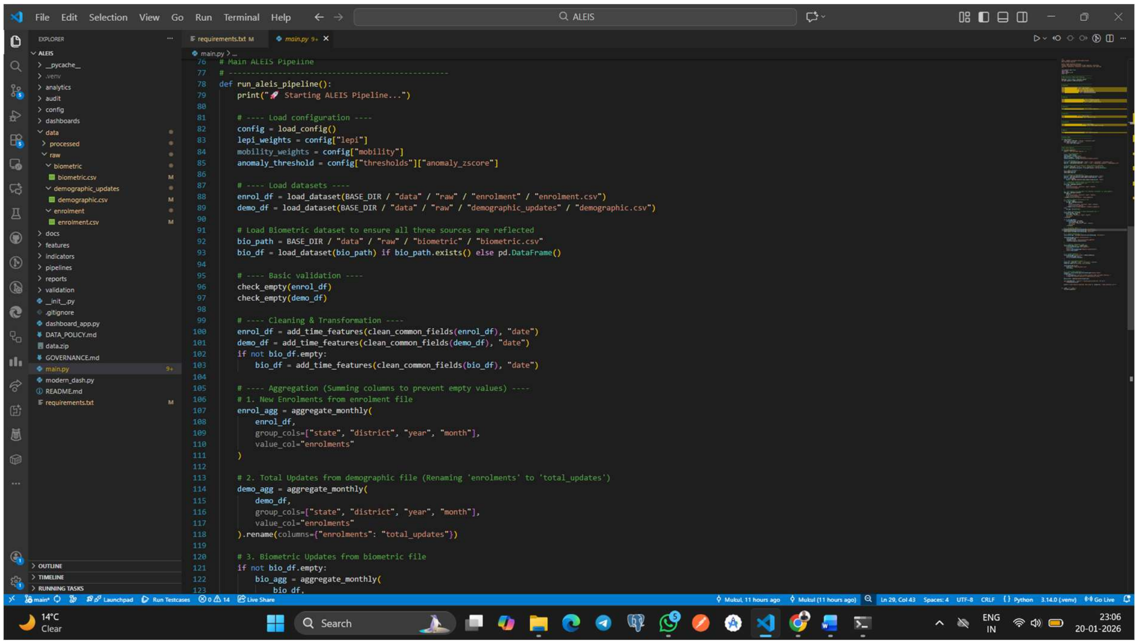
ALEIS demonstrates that Aadhaar update data when analyzed beyond static counts can function as a real-time societal sensor. By modeling behavioral signals and introducing the Life-Event Probability Index, the system enables early-warning intelligence that supports responsive, data-driven governance.

This project highlights the potential of administrative data to move from record-keeping systems to strategic intelligence platforms, unlocking new avenues for informed policymaking at scale.

10. Future Enhancements

- Integration of external indicators (employment, mobility, census)
- Advanced anomaly detection using probabilistic models
- Predictive forecasting of regional demographic shifts
- Real-time dashboard deployment

11. Github Repo - https://github.com/geeky-bhawuk-arora/aadhaar-life-event-intelligence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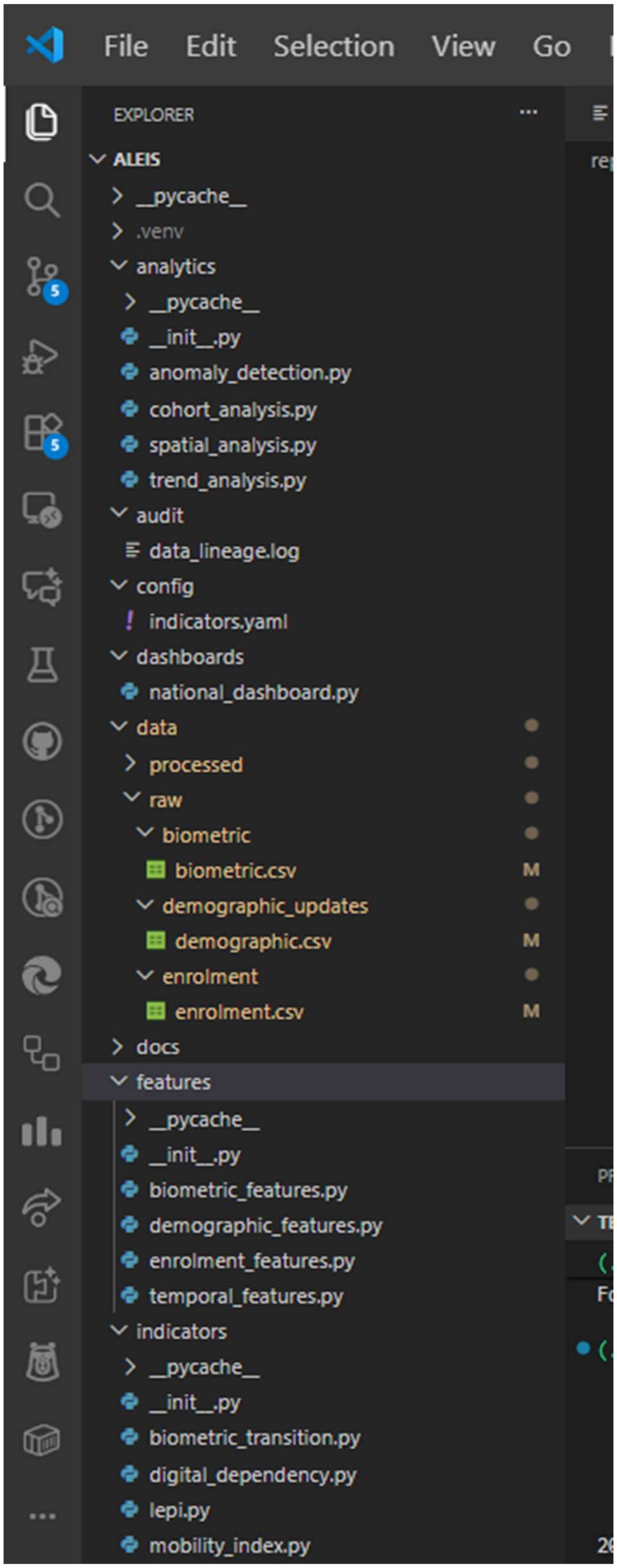
ALEIS
requirements.txt M
main.py 9+
# Main ALEIS Pipeline
# ---
def run_aleis_pipeline():
print("🚀 Starting ALEIS Pipeline...")
# ---- Load configuration ----
config = load_config()
lepi_weights = config["lepi"]
mobility_weights = config["mobility"]
anomaly_threshold = config["thresholds"]["anomaly_zscore"]
# ---- Load datasets ----
enrol_df = load_dataset(BASE_DIR / "data" / "raw" / "enrolment" / "enrolment.csv")
demo_df = load_dataset(BASE_DIR / "data" / "raw" / "demographic_updates" / "demographic.csv")
# Load Biometric dataset to ensure all three sources are reflected
bio_path = BASE_DIR / "data" / "raw" / "biometric" / "biometric.csv"
bio_df = load_dataset(bio_path) if bio_path.exists() else pd.DataFrame()
# ---- Basic validation ----
check_empty(enrol_df)
check_empty(demo_df)
# ---- Cleaning & Transformation ----
enrol_df = add_time_features(clean_common_fields(enrol_df), "date")
demo_df = add_time_features(clean_common_fields(demo_df), "date")
if not bio_df.empty:
bio_df = add_time_features(clean_common_fields(bio_df), "date")
# ---- Aggregation (Summing columns to prevent empty values) ----
# 1. New Enrolments from enrolment file
enrol_agg = aggregate_monthly(
enrol_df,
group_cols=["state", "district", "year", "month"],
value_col="enrolments"
)
# 2. Total Updates from demographic file (Renaming 'enrolments' to 'total_updates')
demo_agg = aggregate_monthly(
demo_df,
group_cols=["state", "district", "year", "month"],
value_col="enrolments"
).rename(columns={"enrolments": "total_updates"})
# 3. Biometric Updates from biometric file
if not bio_df.empty:
bio_agg = aggregate_monthly(
bio_df,
Run Testcases
Live Share
Search
14°C
Clear
ENG
IN
23:06
20-01-2026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trend_analysis.py
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national_dashboard.py
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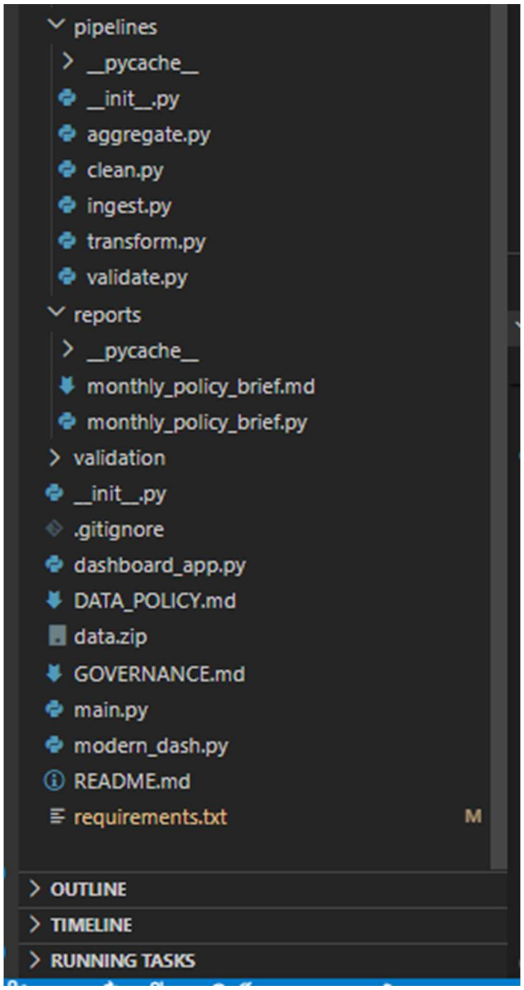
lepi.py
mobility_index.py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validation
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.gitignore
dashboard_app.py
DATA_POLICY.md
data.zip
GOVERNANCE.md
main.py
modern_dash.py
README.md
requirements.txt
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OUTLINE
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RUNNING TASKS