Drift-Aware Process Mining for Loan Processing Systems: A Framework for Detecting and Managing Concept Drift in Digital Lending and Microfinance Operations

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Abstract. In recent years with the emergence of digital transformation banking and financial service sectors are mostly affected and particularly loan and microfinance operations. With frequent regulatory changes and updates, credit assessment policies, and increasing adoption of automated verification technologies have introduced continuous changes in loan approval workflows.These evolving process lead to concept drift, where historical process models become outdated and misaligned with current execution behavioral This paper investigates the impact of concept drift in loan processing systems using process mining techniques. A real-world problem of increased loan turnaround time and inconsistent approval outcomes in digital lending environments is analyzed. We propose an adaptive, drift-aware process mining framework for detecting and managing concept drift using event log data. The framework enables early identification of structural, behavioral, and performance-related changes in loan workflows and supports continuous process adaptation through dynamic model updates. The proposed approach improves Indian banking operational visibility, ensures compliance with evolving policies, and enhances decision consistency in loan processing in an adaptive process mining framework for detecting and handling concept drift using event logs. The proposed solution enables early identification of operational changes and supports continuous process optimization. The study demonstrates how drift-aware process mining can improve compliance, efficiency, and decision consistency in Indian loan processes.

Keywords: Process Mining· Concept Drift· Loan Processing· Digital Lending Microfinance· Indian Banking· Event Logs· Adaptive Process Models

1 Introduction

The Indian financial sector has gone through major changes in recent years. Digitization, regulatory reforms, and financial inclusion programs have reshaped the way banks and non-banking financial companies (NBFCs) operate. Nowdays, most lenders use digital systems to process loan applications, automated tools to assess creditworthiness, and alternative data sources to make faster approval decisions. These changes have made loans easier to access and have reduced processing time. At the same time, frequent updates to these systems and policies often change how the work is carried out, making loan processes less stable and more difficult to predict over time.

Process mining is a technique that uses data to understand how business processes are actually performed. It builds process models from event logs created by information systems. Unlike written procedures, these models show the real flow of work, including delays, variations, and inefficiencies. Traditional process mining methods usually assume that processes remain stable, but in fast-changing environments such as loan processing in India, this assumption often does not hold. Regulatory changes, internal policy updates, and new digital tools often modify workflows, sometimes subtly and sometimes significantly. These ongoing changes lead to what is known as concept drift, where the behavior of a process evolves over time.

Several recent studies show that concept drift can seriously affect the accuracy of process mining results. When workflows change, previously discovered models no longer represent reality. This can lead to incorrect performance analysis, failure to detect compliance violations, and poor operational decisions. If drift is not identified in time, organizations may continue to rely on outdated insights, reducing the value of process analytics.

Loan processing in India faces additional challenges due to frequent regulatory and technological interventions. Initiatives such as Aadhaar-based e-KYC, GST data integration for income verification, the Account Aggregator framework, and the introduction of Video KYC have fundamentally changed how loans are sourced, verified, approved, and disbursed. Each new regulation or digital innovation introduces changes in the process flow, creating multiple points where concept drift can occur.

This paper examines concept drift in Indian loan processes and proposes a drift-aware process mining framework to handle evolving workflows more effectively. The key contributions of this work are fourfold. First, it analyzes the major sources of concept drift in Indian digital lending and microfinance operations and explains their operational impact. Second, it presents a structured framework for detecting, locating, and managing process drift using event log data. Third, it outlines evaluation metrics and an experimental design to assess the effectiveness of drift detection techniques. Finally, the paper offers practical guidance for financial institutions seeking to implement drift-aware process mining in real-world lending environments.

2 Background and Related Work

2.1 Concept Drift in Process Mining

Concept drift refers to changes in the process behavior, structure, or performance over time. In the context of process mining, drift manifests as alterations in activity sequences, resource allocations, timing patterns, or decision rules that govern process execution. The seminal work by Bose et al. [4] established foundational methods for detecting drift in business processes by analyzing statistical changes in trace characteristics across time windows. Concept drift in process mining can be classified into four primary categories based on the nature of change [2, 5]. Sudden drift occurs when the process changes abruptly at a specific point in time, typically due to regulatory mandates or system upgrades. Gradual drift involves a slow transition where both old and new process variants coexist for a period before the new variant dominates. Incremental drift represents continuous small-scale changes that accumulate over time, often resulting from organic process optimization. Recurring drift describes cyclical patterns where the process alternates between different variants, commonly observed in seasonal business operations. Recent surveys emphasize the importance of adaptive and online approaches to handle drift effectively in streaming environments [1]. Frameworks such as CONDA-PM provide structured approaches to analyze and localize changes in business processes [5]. Adams et al. [6] introduced explainable drift detection methods that not only identify when drift occurs but also provide interpretable descriptions of what changed, facilitating targeted remediation. However, most existing studies focus on generic business processes and lack domain-specific applications in financial services, particularly in emerging markets like India.

2.2 Digital Transformation in Indian Loan Processing

2.2.1 Concept Drift in Process Mining Concept drift refers to changes in the process behavior, structure, or performance over time. In the context of process mining, drift manifests as alterations in activity sequences, resource allocations, timing patterns, or decision rules that govern process execution. The seminal work by Bose et al. [4] established foundational methods for detecting drift in business processes by analyzing statistical changes in trace characteristics across time windows. Concept drift in process mining can be classified into four primary categories based on the nature of change [2, 5]. Sudden drift occurs when the process changes abruptly at a specific point in time, typically due to regulatory mandates or system upgrades. Gradual drift involves a slow transition where both old and new process variants coexist for a period before the new variant dominates. Incremental drift represents continuous small-scale changes that accumulate over time, often resulting from organic process optimization. Recurring drift describes cyclical patterns where the process alternates between different variants, commonly observed in seasonal business operations. Recent surveys emphasize the importance of adaptive and online approaches to handle drift effectively in streaming environments [1]. Frameworks such as CONDA-PM provide structured approaches to analyze and localize changes in business processes [5]. Adams et al. [6] introduced explainable drift detection methods that not only identify when drift occurs but also provide interpretable descriptions of what changed, facilitating targeted remediation. However, most existing studies focus on generic business processes and lack domain-specific applications in financial services, particularly in emerging markets like India.

2.2.2 Digital Transformation in Indian Loan Processing Indian lenders have increasingly adopted digital technologies for loan origination, e-KYC, automated credit checks, and digital disbursement. The Digital India initiative and India Stack infrastructure have enabled unprecedented digitization of financial services [3]. Microfinance institutions (MFIs) and banks now rely on mobile devices and digital platforms to streamline loan approvals and repayments, extending financial services to previously underserved populations. Studies show that nearly all disbursements in India are now conducted digitally, with mobile-based loan origination becoming the norm rather than the exception [7]. The Account Aggregator framework, launched in 2021, enables consent-based financial data sharing across institutions, fundamentally changing how creditworthiness is assessed. Similarly, the adoption of Video KYC during the COVID-19 pandemic has created new verification workflows that exists in modified forms today. Such rapid digital adoption leads to evolving process variants, which makes loan workflows highly susceptible to concept drift. Unlike traditional banking environments where the processes remain stable for years, Indian digital lending operates in a state of continuous evolution. This creates challenges in maintaining consistent approval , regulatory compliance, and risk assessment accuracy. The Reserve Bank of India's frequent regulatory updates further contribute to process volatility, as institutions must quickly adapt their workflows to remain compliant.

2.3 Research Gap

Despite the growing body of literature on concept drift detection and the significant transformation of Indian financial services, limited research addresses their intersection. Existing drift detection methods have primarily been validated on synthetic datasets or manufacturing processes, with few applications in financial services [1, 2]. The unique regulatory environment, rapid digitization, and financial inclusion priorities of Indian banking have not been systematically studied from a process mining perspective. This paper addresses this gap by proposing a domain-specific framework for drift-aware process mining in Indian loan processing systems.

3 Methodology

3.1 Description

A key current problem in Indian loan processing is the frequent change in loan approval and verification workflows due to digital policy updates and regulatory changes. These changes affect multiple process dimensions and create hidden concept drift in event logs that degrades operational performance. The primary sources of drift in Indian loan processing include: Digital KYC and Re-verification Requirements: The RBI has issued multiple circulars modifying KYC requirements, including the introduction of Video KYC (V-CIP), periodic re-verification mandates, and Aadhaar-based authentication changes. Each update triggers workflow modifications that alter activity sequences, resource allocations, and timing patterns. Alternative Credit Scoring Rules: The emergence of credit bureaus, alternative data sources, and AI-based scoring models has created heterogeneous credit assessment workflows. Different customer segment may follow different credit scoring paths, and the introduction of new scoring parameters creates incremental drift in decision logic. Risk Policy Changes in Microfinance: Microfinance institutions regularly adjust their risk policies to match changing conditions. These changes are often based on repayment trends, regional risk factors, and new regulatory guidelines. Because of this, loan size limits, interest rates, and recovery methods are updated frequently. Over time, these updates slowly change how loan applications move through the system, leading to repeated shifts in the overall process. Automated Fraud and Compliance Checks: Many lenders use automated systems to check for fraud, ensure AML/CFT compliance, and verify documents. While these systems improve safety and compliance, they also add new steps and decision points to the loan process. When fraud rules or compliance criteria are updated, the process flow changes automatically, even if the overall loan process design remains the same

3.2 Proposed Framework

The figure 1 describes the overall architecture of the drift aware process mining framework designed to monitor, evaluate and also adapt the entire loan processing. The above architecture follows a systematic layered pipeline approach, enabling continuous detection and handling of concept drift. Loan Management System (Data Source Layer) block represents operational systems such as loan origination platforms, credit assessment systems, and verification modules. These systems generate raw execution data at the time of loan application processing. Event Log Extraction Module component extracts execution traces from databases and transforms the operational databases into structured event logs. Each event captures important attributes such as case identifier, activity name, timestamp, resource, and contextual information. Preprocessing and Standardization Layer extracts and then these extracted logs are cleaned and standardized by handling noise, missing values, and inconsistent activity labels. Then the logs are formatted according to the standard representations (e.g, XES) to ensure

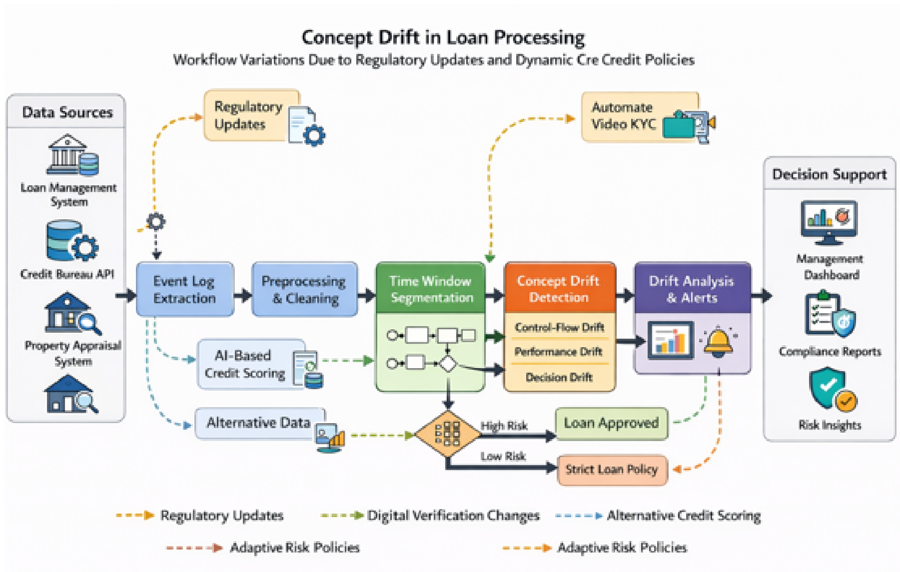

Fig. 1. System Architecture

compatibility with process mining techniques. Baseline Process Discovery is a reference process model discovered from historical event logs representing stable system behavior. This model serves as the baseline for detecting deviations and is typically expressed using BPMN or Petri nets. Online Concept Drift Detection Engine This core component continuously analyzes incoming event logs using time-based windows. It monitors statistical, structural, and behavioral changes in the process to detect potential concept drift. Drift Localization and Analysis Module Once drift is detected, this module identifies the specific subprocesses, activities, or decision points affected by the change. Localization enables targeted investigation rather than full process reanalysis. Adaptive Model Update Module Based on the detected drift type (sudden, gradual, incremental, or recurring), the system updates the process model either through full rediscovery or incremental adaptation. Performance and Compliance Monitoring Dashboard The final block visualizes key performance indicators (KPIs), compliance metrics, and

3.3 Consequences of Undetected Drift

When concept drift goes undetected in loan processing systems, several operational problems emerge:

1. Outdated Process Models: With time, process models may no longer reflect how the work is actually performed. When this happens, conformance checks

become less useful and process reports may give a misleading picture. Decisions may still be based on these outdated models even though the real process has changed.
2. Longer Processing Time: Minor inefficiencies caused by unnoticed process changes gradually build up, increasing the time required for loan approvals. In many cases, these delays are attributed to staffing or workload issues instead of changes in the workflow itself.
3. Inconsistent Approval Decisions: When decision rules or scoring methods are modified, approval results may vary. Similar loan applications processed at different times can receive different outcomes, which may affect perceptions of fairness and customer trust.
4. Compliance Gaps: Regulatory updates are not always implemented consistently across all process paths. If process changes are not monitored, older workflows may continue alongside updated ones, leading to potential compliance risks.
5. Hidden Bottlenecks: As processes change, some bottlenecks disappear and new ones appear. Standard monitoring systems may fail to capture these shifts, causing organizations to focus on outdated problem areas while new constraints remain unnoticed.

3.4 Impact Assessment

The operational impact of concept drift in Indian loan processing extends across multiple dimensions:

Table 1. Operational Impact of Concept Drift in Loan Processing

Impact Area	**Manifestation**	**Business Consequence**
Process Efficiency	Increased manual interventions, rework loops	Higher processing costs, delayed disbursements
Compliance	Undetected deviations from current regulations	Regulatory penalties, audit findings
Customer Experience	Unpredictable approval timelines	Customer complaints, application abandonment
Risk Management	Outdated risk assessment models	Increased default rates, portfolio quality decline
Operational Visibility	Misalignment between dashboards and reality	Poor decision-making, resource misallocation

4 Proposed Solution: Drift-Aware Process Mining Framework

This paper introduces a flexible framework for detecting and managing process changes in Indian loan processing systems. The framework works on continuously generated event data and allows ongoing monitoring to identify when changes occur, where they happen in the process, and how they can be addressed.

4.1 Framework Architecture

The proposed framework consists of six integrated components that form a continuous monitoring and adaptation pipeline:

Table 2. Framework Components and Functions

Component	Function	Output
Event Log Extraction	Collect and standardize event data from LMS	XES-formatted event logs
Baseline Process Discovery	Generate reference process model	BPMN/Petri net model
Online Drift Detection	Monitor for statistical and structural changes	Drift alerts with timestamps
Drift Localization	Identify affected subprocesses and activities	Change impact report
Adaptive Model Update	Regenerate models reflecting new behavior	Updated process models
Performance Monitoring	Track KPIs and compliance metrics	Operational dashboards

4.2 Event Log Extraction

The framework starts by collecting event log data from Loan Management Systems (LMS) and other related operational databases. Each event entry includes the loan application ID (case ID), the activity performed, the time of the event, the staff member or system involved, and additional details such as loan type, loan amount, and applicant category. The data is extracted in the IEEE XES (eXtensible Event Stream) format so that it can be easily used with standard process mining tools. Critical activities captured in loan processing event logs include: application submission, document upload, KYC verification (with sub-activities for Aadhaar, PAN, and address verification), credit bureau check, credit score calculation, risk assessment, manual review (if triggered), approval/rejection decision, documentation, and disbursement. Each activity is timestamped with start and completion times where available, enabling both control-flow and performance analysis.

4.3 Baseline Process Discovery

The baseline process model serves as the reference against which drift is detected. We employ the Inductive Miner algorithm for initial process discovery due to its guarantees of producing sound models and its ability to handle infrequent behavior appropriately [8]. The discovered model represents the process structure during a defined baseline period when the process is considered stable and representative. For Indian loan processing, separate baseline models may be maintained for different loan products (personal loans, home loans, MSME loans, microfinance) as these follow distinct workflows. The baseline period selection is critical; it should represent normal operations without known disruptions or recent regulatory changes. Typically, a 3-6 month baseline period provides sufficient data while avoiding historical drift contamination.

4.4 Online Drift Detection

The drift detection module combines multiple detection methods to reliably identify process changes while keeping false alerts under control.

1. Statistical Feature Monitoring: Key process indicators such as activity frequency, step transitions, case completion time, and resource usage are continuously monitored. Adaptive windowing techniques are used so that the observation window automatically adjusts when changes occur. The ADWIN (Adaptive Windowing) algorithm helps balance quick detection with stability by resizing windows based on detected shifts [9]. When a significant change is observed in any monitored feature, the system raises a drift alert.
2. Control-Flow Similarity Analysis: At set intervals, new process models are generated using recent event data and then compared with the baseline model. If the similarity between the two models drops noticeably, it indicates that the process structure may have changed. To keep the analysis fast the system first uses simple footprint based comparisons. When these initial checks suggest a possible change, a more detailed graph-edit distance analysis is performed to examine the structural differences more closely.
3. Behavioral Relation Tracking: The framework tracks relationships between activities, including direct succession, eventual succession, parallel execution, and exclusive behavior. Any change in these relationships signals a modification in process logic. This method, adapted from the ProDrift approach [10], allows precise identification of where changes are occurring within the process.

4.5 Drift Localization

Upon drift detection, the localization component identifies which specific subprocesses, activities, or decision points are affected. This targeted analysis enables efficient investigation and remediation. Localization techniques include:

1. Subprocess Isolation: The loan process is divided into logical subprocesses (application intake, verification, credit assessment, decision, fulfillment) and drift analysis, is performed independently on each subprocess to isolate the changed location.

2. Activity-Level Analysis: Changed individual activity frequencies, durations, or preceding/succeeding activities are scrutinised to recognise specific activities affected by drift.
3. Decision Point Examination: Process branches represented by decisions (approve/reject, manual review trigger, documentation requirements) are analyzed for changes in branched probabilities or decision criteria.

4.6 Adaptive Model Update

When drift is confirmed and localized, the framework supports multiple adaptation strategies based on drift type and organizational preferences: For sudden drift, complete model rediscovery using post-drift data is recommended. This approach is correct when regulatory changes mandate modifications in the immediate processes, and the old process variant should not influence the new model. For gradual drift, incremental model updates are blended in historical and recent behavior to provide smoother transitions. The framework maintains weighted process variants and adjusts weights based on observed frequencies. For recurring drift, the framework , a library of process variants indexed by temporal or contextual triggers is maintained (e.g., month-end processing, festival season variants). Automatic variant switching based on detected patterns reduces manual intervention.

4.7 Performance and Compliance Monitoring

The final component caters continuous monitoring of key performance indicators (KPIs) and compliance metrics. Standard loan processing KPIs monitored include:

Table 3. Key Performance Indicators for Loan Process Monitoring

KPI Category	Metric	Target Direction
Efficiency	Loan Turnaround Time (TAT)	Minimize
Efficiency	First-Pass Approval Rate	Maximize
Efficiency	Rework/Resubmission Rate	Minimize
Compliance	KYC Completion Rate	Maximize (100%)
Compliance	Regulatory Deviation Count	Minimize (0)
Quality	Post-Disbursement Error Rate	Minimize
Customer	Application Abandonment Rate	Minimize

5 Experimental Design

To validate the proposed framework, we design a comprehensive experimental study using real-world loan processing data from Indian financial institutions.

5.1 Data Sources

A case study approach is proposed using event logs from three types of Indian financial institutions representing different loan processing contexts:

1. Public Sector Bank: Large-scale operations with established processes, subjected to government policy influences and serving diverse customer segments including priority sector lending.
2. Private NBFC: Technology-driven operations with frequent process innovations, higher digitization levels, focus on consumer and small business lending.
3. Microfinance Institution (MFI): High-volume, low-value loan operations with mobile-first processes, serving financially deprived populations with unique verification and collected workflows.

Event logs spanning 24-36 months would capture multiple potential drifts events including regulatory changes, technology upgrades, and seasonal variations. Data anonymization would remove personally identifiable information while preserving process characteristics necessary for analysis.

5.2 Evaluation Metrics

Framework performance would be evaluated using the following metrics:

1. Drift Detection Accuracy: Measured as F1-score combining precision (proportion of detected drifts that are true drifts) and recall (proportion of true drifts that are detected). Ground truth would be established through expert annotation and correlation with known change events.
2. Detection Delay: Time elapsed between actual drift occurrence and framework detection. Earlier detection enabled faster response and reduced operational impact.
3. Localization Precision: Accuracy in identifying the specific subprocess or activity affected by drift, validated against expert analysis of known changes.
4. Operational Impact: Measurable improvements in process performance after drift-aware intervention, including reduction in TAT variability, improvement in first-pass approval rates, and decrease in compliance deviations.

5.3 Baseline Comparison

The proposed framework would be compared against:

1. Static Process Mining: Traditional process discovery without drift detection, represented current practices at most institutions.
2. Fixed-Window Detection: Drift detection using fixed time windows without adaptive sizing, represented a simpler statistical approach.
3. Manual Review: Periodic (monthly/quarterly) process analysis by analysts, representing current best practice at process-mature organizations.

6 Discussion

The proposed framework addresses a critical gap in Indian loan operations by enabling continuous monitoring of evolving workflows. Unlike static process mining approaches that assumed process stability, drift-aware analysis reflected real-time operational changes and maintains model accuracy despite environmental volatility.

6.1 Theoretical Contributions

This study adds to existing process mining research by applying drift detection techniques to financial services. The proposed framework uses multiple detection methods, which helps in identifying different kinds of process changes such as sudden shifts, slow transitions, gradual adjustments, and recurring patterns. This is especially important in Indian loan processing, where workflows change often and in different ways. The framework also adapts general drift detection techniques to suit financial processes. It takes into account practical factors such as regulatory compliance, risk-based decision-making, and service quality expectations. By focusing on the Indian banking environment—shaped by regulations, digital lending initiatives, and financial inclusion goals—this work offers a useful reference for other emerging markets that are also experiencing rapid digital growth in financial services.

6.2 Practical Implications

For financial institutions, the framework offers several practical benefits:

1. Early Warning System: The framework can spot changes in loan processes within days instead of weeks or months. This allows institutions to act early, rather than responding after problems escalate. Potential issues can be examined and fixed before they affect customers or lead to regulatory concerns.
2. Better Compliance Control: Ongoing monitoring of process changes helps demonstrate stability during audits and regulatory reviews. When changes are detected, the framework helps pinpoint where they occur, making it easier to focus compliance checks on specific areas instead of reviewing the entire process.s.
3. Process Improvement Enablement: he framework helps separate planned process changes from unexpected or harmful ones. Organizations can confirm whether new initiatives are working as intended, while negative changes can be identified early and corrected if needed.
4. Resource Optimization: By clearly showing which parts of the process are affected by change, institutions can focus training, system updates, and staffing efforts where they are actually needed. This avoids broad fixes that consume time and effort without addressing the real problem.

6.3 Limitations and Future Work

A few limitations of this work should be noted. First, the framework depends on the availability of detailed and reliable event logs. Financial institutions with disconnected systems or low-quality data may find it difficult to apply the approach effectively. Second, the experimental setup proposed in this study has not yet been implemented. Testing the framework using real operational data would help demonstrate its practical value and reliability. Future research can build on this work in several ways. One important extension would be integrating the framework with live loan management systems, allowing organizations to respond automatically when process changes are detected. Applying machine learning techniques to classify different types of process changes could also help suggest suitable actions for each situation. In addition, studying data across multiple financial institutions could reveal common patterns of process change in Indian banking, supporting benchmarking and the sharing of best practices across the industry.

7 Conclusion

This paper points out that concept drift is an important issue in Indian loan processing, but it is often overlooked. Rapid digitization, frequent regulatory changes, and shifting customer behavior mean that loan processes in India do not remain stable for long. In such conditions, traditional process mining methods that assume fixed workflows can lead to incorrect or misleading conclusions. To address this problem, the paper introduces a drift-aware process mining framework. The framework continuously monitors event log data, applies multiple techniques to detect process changes, identifies where those changes occur, and updates process models accordingly. By keeping process views aligned with real execution, financial institutions can improve efficiency, stay compliant with regulations, and offer more consistent service to customers. As banks and NBFCs in India continue to adopt digital lending platforms, the ability to identify and manage process changes becomes increasingly important. The framework presented in this study offers a structured way to build this capability. Future research will focus on testing the framework at scale using real operational data and integrating it with live loan management systems to demonstrate its effectiveness in real-world settings. The relevance of this work is not limited to India. Financial institutions around the world face similar challenges due to rapid digital adoption, changing regulations, and evolving processes. The approach demonstrated in this paper shows how drift detection techniques can be adapted to specific domains, providing a useful reference for other markets and industries where business processes change faster than traditional analytical methods can handle.

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