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Implementing the Abnormal Detection in Financial Transaction through Concept Drift using CUSUM algorithm

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Abstract- There is a significant amount of use of models that are founded on artificial intelligence (AI) in the banking business for a variety of applications. The monitoring of monetary transactions, the assessment of credit risk, and the identification of fraudulent activity are all examples of applications that fall under this category. However, it is possible that the performance of these models will worsen over the course of time as a result of changes in the patterns of the data that is being received. It is not impossible for this phenomenon, which is referred to as concept drift that the reliability and accuracy of artificial intelligence forecasts will considerably drop when the statistical distribution of real-time data differs from the data that was used during model training. As a result of this research, an Automatic Monitoring System that can detect abnormal data patterns in banking environments has been developed. Concept drift detection techniques are what make this system conceivable. This system is designed to recognize data patterns that are not normal in order to carried out with the intention of finding a solution to the problem. The system that has been built is capable of carrying out continuous monitoring of the data streams that are constituted of financial transactions. A statistical drift detection method that is based on the Cumulative Sum (CUSUM) algorithm is utilized in order to discover substantial deviations from the patterns that are generally observed. This will allow for the identification of major deviations. This method is utilized in order to detect deviations that are statistically significant in order to achieve the desired results. For the purpose of determining the cumulative changes that have taken place in the distribution of the data, this methodology is applied. When the deviation is more than a level that has been defined, the system will automatically recognize the occurrence as a possible idea drift and will send warnings to the administrators of the system in order to tell them of the issue. The alert mechanism comprises a number of different kinds of automatic notifications. Due to the fact that it receives these notifications, it is able to take corrective actions and intervene in a timely manner, both of which are extremely significant. There is a dataset that is comprised of simulated financial transactions that is utilized for the goal of determining whether or not the system that has been presented is effective. This dataset contains a variety of parameters that are pertinent to the behavior of transactions and the prediction of fraudulent activity. The employment of artificial intelligence is what allows for the successful fulfillment of this objective successful.

Keywords: Artificial Intelligence, Concept Drift Detection, Banking Systems, CUSUM Algorithm, Abnormal Data Pattern Detection, Fraud Monitoring, Real-Time Data Monitoring, Automated Alert System

1. INTRODUCTION

sector is increasingly harnessing the capabilities of Artificial Intelligence (AI). Financial institutions rely on AI technology for fraud detection, customer interaction through chatbots, credit risk assessment, and algorithmic trading. However, the datasets that AI systems utilize in the banking sector are precarious and constantly changing. Non-stationarity arises due to a wide variety of economic factors such as changing customer sentiment, ever-growing and changing policies and regulations, the economic environment, and new and innovative approaches of scammers.

A. Background of Concept Drift

Concept drift is the change of the learned statistical dependence, therefore, the relationship linking the input features with the target variable changing is also concept drift. Basically, a model is accurate to a business's "truth" as

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defined by history. If a model fetches a "truth" and that "truth" is no longer valid, the model would be inaccurate. This phenomenon is quite harmful in the implementation of AI in finance as the industry is very dynamic. The fast pace of fraudsters are always coming up with new ways to steal money and steal financial transactions. It draw attention to the need for ways to find drift as it happens, allowing timely and successful interventions to take place. The point of this paper is to find current research gaps in AI concept drift detection in real time models used in the banking industry by looking at recent university research and reports on the business.

B. Existing system

Shahapurkar et. al. (2023), proposed ML-based fraud detection pipeline (using XGBoost) with drift detection modules. Demonstrated robustness: their system outperforms standard static models in presence of evolving data streams, in terms of accuracy, precision, recall. -The drift-aware model maintains performance over multiple days, adapting to changes over time. Relies on labelled data for drift detectors; drift detection in supervised manner may not handle unlabeled data or delayed labels. If drift detection triggers adaptation too late, there may be a lag risk of misclassifications before retraining/adjustment. Frequent retraining or updating may increase computational cost, complexity, and risk of overfitting to recent data.

Feng et. al. (2024), defines concept drift formally: over time, relationship between input and target may change, invalidating static models. Classifies many adaptation strategies: online learning, ensembles, window-based retraining, model reuse, etc. -Highlights that adaptive learning is essential: static learning leads to degradation with drift; adaptation restores or maintains predictive performance. Many adaptation methods assume timely availability of ground truth labels — sometimes unrealistic in real-world streams (delays, privacy, labeling cost). Frequent retraining / adaptation introduces computational overhead; not all algorithms scale well. Stability–plasticity dilemma: balancing adaptability (plasticity) with retention of past knowledge (stability) is hard; naive updating can cause catastrophic forgetting.

Xiang et al. (2023), introduces a novel approach using a ML (object-detection inspired) model to detect various types of drift: sudden, gradual, incremental, recurring and covering broader spectrum than many existing detectors that target only some drift types. Demonstrates that ML-based detectors can outperform classical statistical detectors especially in complex, high-dimensional or noisy stream environments. Requires labeled event logs with drift instances to train detector not always easy in real-world contexts. It may be sensitive to noise or mislabelled data; performance depends on quality and representativeness of training logs. Detection in offline / event-log context — may not work in all real-time streaming scenarios with latency or partial labeling.

Kraus et al. (2025), survey shows deep-learning methods (discriminative, generative, hybrid, transfer, continual learning) are being adapted for concept drift. Drift-aware DL models can better handle complex, non-linear relationships and varying data distributions — more flexible than classical ML. Demonstrates feasibility of drift adaptation with DL: model updates, hybrid strategies, periodic retraining or adaptive parameter updates. (MDPI). Deep models tend to be computationally heavy; continuous adaptation / retraining in real-time streams can be resource-intensive. Data-hungry — require significant data to retrain reliably; in drift conditions, acquiring enough recent labeled data may be difficult.- Risk of catastrophic forgetting or overfitting to latest data if adaptation not managed properly.

C. Research Gaps

A significant amount of work needs to be done in the area of developing real-time concept drift detection algorithms that are able to deal with the extremely unequal data distributions that occur frequently in the banking industry. When it comes to identifying fraudulent loabelctivity and determining the level of credit risk, this is especially true. It is possible to discover changes in patterns of weird events using a wide variety of various ways; however, many of these methods are not very effective at what they are trying to accomplish. It is important that any new studies investigate ways to better deal with change in the minority class demographic. An additional significant area of research that requires our attention is the development of real-time concept drift tracking technologies that are easy to comprehend for banking artificial intelligence. Considering the stringent regulations and the requirement for distinct financial options, it is essential to devise methods that not only identify drift but also provide a description of it and an explanation of the factors that contribute to it. Researchers should investigate algorithms that discover drift in a way that is naturally intuitive or investigate how experts employ Explainable Artificial Intelligence (XAI) techniques in order to improve

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the ways that are now being used in real time. Federated learning is being utilized in order to locate financial institutions that have forgotten how to learn about a new topic. In order to determine the most effective methods of catering to the many sorts of clients and banks that have locations all over the place, additional study is required. Each each member of the federation possesses a unique set of drift characteristics. This is something that has to be rectified, and the drift tracking process needs to be expedited quickly while yet maintaining individual privacy. For the time being, the majority of study is simply focusing on figuring out how to identify concept drift. When an idea drift is discovered, it is of utmost importance to rectify the situation as soon as possible and to take action. We need to develop a means to alter models in real time so that performance can remain high and we can even find any gaps before they have a significant impact on how well banking AI systems function with regard to their overall performance. Furthermore, there is a significant gap in the research because there are no comprehensive evaluation frameworks or clear criteria in place to determine the effectiveness of real-time tools for identifying idea drift in the banking business. This is a significant limitation of the study. It is of utmost importance to develop frameworks that take into consideration the manner in which the banking industry operates with data and standards. Consequently, this will make it possible to compare various methodologies in an objective manner and will propel the subject forward.

D. Objectives

To implement an Automatic Monitoring System to Raise Alerts on Abnormal Data Pattern - This objective is to design and implement a real-time concept drift detection framework to ensure the reliability of AI models used in banking. By identifying changes in data patterns over real time and alert stakeholder about drift via SMS, Beep or E-mail.

E. Scope of research

AI is now an important part of modern banks. Changing how things are done in many areas, like credit monitoring and fraud spotting scoring, algorithmic trading, tailored customer service, and fighting money laundering money laundering (AML) and managing risks. These AI models, which are often complicated groups that use machine learning are trained on very large sets of data to find patterns, guess what will happen, and make choices automatically. The first deployment of a well-trained model usually leads to big improvements in speed and being efficient. But things in the banking world aren't always the same. The economy changes, customer tastes change, and new financial new goods come out, rules and regulations are updated, and bad people do bad things. They are always changing their strategies. These powerful forces will always result in a difference between the data set that an AI model was trained on and the info that it receives during production. In this difference, radically changing how input features and goal features are related idea drift is the term for this. What it means for ideas to move without being noticed in Banking problems are bad. A model that used to be very good at finding theft might start not noticing new fraud trends leads to big financial losses. The scoring model might put borrowers in the wrong category, which would raise the rate of failure. An AML system might not notice transactions that look fishy, leaving the bank open to Penalties from the government and damage to your image. Because of this, the power to and being able to respond to idea drift in real time is not just a nice-to-have for operations, a critical must for keeping the effectiveness, dependability, and following the rules for using AI in banks.

II. MATERIALS AND METHODS

An AI model for banking that can detect idea drift: In order to ensure that machine learning models are consistently accurate and dependable in the banking industry, which is constantly evolving, it is necessary to identify an AI model that can detect idea drift. It assists banks in implementing modifications to their systems while maintaining their efficiency by identifying changes in data trends that are not immediately apparent.

Mathematical Model for Concept Drift Detection

Concept drift occurs when the **statistical properties of the data change over time**.
Assuming, Xt=incoming data stream at time t, μ=mean of baseline data, k=drift sensitivity parameter, St=cumulative deviation score

CUSUM Model

CUSUM detects drift by accumulating deviations.

$$St=\max(0, S_{(t-1)} + (Xt - \mu - k) \qquad (1)$$

Where
Xt = current observation, μ = expected mean, k = tolerance level, St = cumulative deviation
1)

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2) C. Drift Detection Condition

Concept drift is detected if **St>h**

Where, h = predefined threshold.

3) D. Alert Condition

If

$$|X_t-\mu|>\delta \qquad (2)$$

then **Abnormal Pattern Alert is triggered,** Where δ = deviation threshold

A. The prevention of fraud and real-time cash flow analysis

A web-based drift detector is a critical component of systems that analyze an infinite quantity of financial data, including trade and deal data. Some of the tasks that the analyst assists institutions with include:

- Develop fraud models that can be adjusted to accommodate various scenarios. The concept of artificial intelligence enables the development of machine learning systems that can detect and mitigate new schemes as they emerge. In this manner, it is feasible to continue acquiring knowledge from new transaction data. This implies that fraud detection will consistently function effectively and be proactive.
- The model can rapidly acquire new methods for identifying frauds when there are modifications to the standard process of conducting transactions. This enables the model to operate in the most optimal manner with real-time input. In general, this approach is effective over time, despite the fact that con artists are constantly devising new methods to deceive individuals.
- Banks may expedite the detection of fraud by employing concept drift recognition to implement model modifications. This results in an increased number of methods for responding to peril. Opt for systems that are based on learning and are capable of adapting, rather than those that have fixed principles. These systems are more adept at addressing emerging hazards.

B. Utilizing big data to identify hazards and ensure that regulations are adhered to

In order to detect criminal activity and ensure that institutions adhere to the law, they must be capable of managing vast quantities of data. What is the reason for the AI model's effectiveness in detecting idea drift? It is capable of analyzing both structured and unstructured data from a variety of sources, including transactions and consumer behavior, in big data systems. This enables you to access a wide range of financial data. This ability enables you to identify intricate fraud patterns that may indicate that things are not proceeding as expected.

- Assisting individuals in adhering to the regulations: Financial institutions can follow rules like Anti-Money Laundering (AML) laws better because the model always looks for data drift. The presence of movement may indicate that suspect behavior has transitioned. This would necessitate an examination and recalibration of the model.
- The model uses anomaly detection to find small links and rising risks that more traditional systems might miss. Threats are now more readily identified prior to their occurrence. This means that there may be a new risk when a change is found. The bank can now take extra steps to protect itself and make the market safer.
- The second principle is to continue learning.

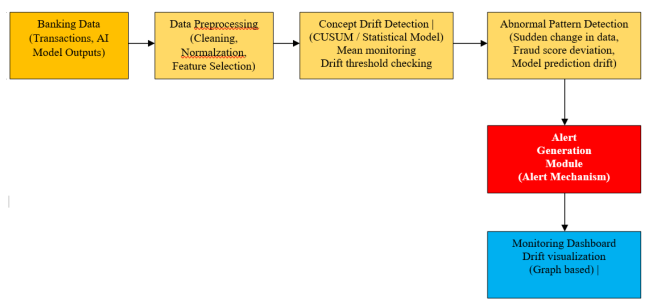

Fig.1 Block diagram of the proposed system

for monitoring banking data to detect fraud or unusual changes in patterns. Here is a short explanation of how the data flows through each stage:

1) Data Input and Preparation

Banking Data: The process starts by collecting raw data, including financial transactions and existing AI model outputs.

Data Preprocessing: The system cleans and normalizes this data (e.g., removing errors or standardizing formats) and selects the most important features for analysis.

2) Detection and Analysis

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Concept Drift Detection: This stage monitors the "mean" or average behavior of the data. It uses statistical models (like CUSUM) to check
if the data's fundamental properties are shifting beyond a set threshold.
Abnormal Pattern Detection: The system looks for specific "red flags," such as sudden changes in transaction data, deviations in fraud
scores, or drifts in model predictions.

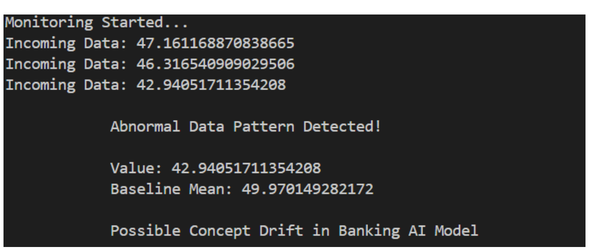
3) Visualization
Alert Generation system: If an abnormal data pattern or abnormal drift is detected, this system generate an alert mechanism to notify the
relevant source

4) Monitoring Dashboard: We can modify through the dashboard type setup using web framework flask to make it more visualized properly and to understand the concept in detailed

The overall workflow of the proposed monitoring system can be summarized as follows:

- User uploads a banking transaction dataset.
- The system validates dataset attributes.
- Transaction data is extracted and preprocessed.
- The CUSUM algorithm analyzes transaction patterns.
- Concept drift is detected if the deviation exceeds the threshold.
- Visualization graphs are generated.
- Alerts are triggered when abnormal patterns occur.
- Results are displayed through the web monitoring dashboard

III. RESULT AND DISCUSSION


```
Monitoring Started...
Incoming Data: 47.161168870838665
Incoming Data: 46.316540909029506
Incoming Data: 42.94051711354208

        Abnormal Data Pattern Detected!

        Value: 42.94051711354208
        Baseline Mean: 49.970149282172

        Possible Concept Drift in Banking AI Model
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Fig.2 Monitoring started

The diagram demonstrates how a monitoring system detects **abnormal input data and potential concept drift** in a banking AI model by comparing incoming values with a baseline mean.

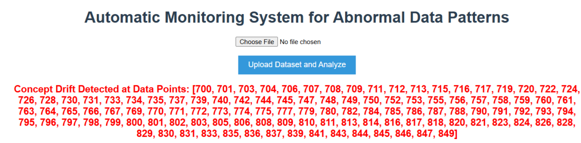

Fig. 3 Concept drift detected at datapoints (Through web framework flask)

The diagram demonstrates that the monitoring system successfully detects and highlights the exact locations in the dataset where concept drift occurs**,** enabling timely alerts and model retraining.

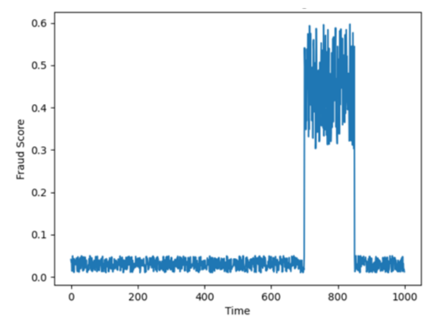

Fig. 4 Fraud Score monitoring

The graph illustrates a temporary abnormal spike in transaction amounts, which can indicate concept drift or suspicious financial activity, triggering the monitoring system to raise alerts.
From time 0 to around 700, the transaction amounts remain relatively stable between 4000 and 7000, indicating normal transaction behavior

- Between time 700 and 850, there is a sudden increase in transaction amounts (around 12,000–20,000), which represents an abnormal pattern or possible concept drift.
- After time 850, the transaction values return again to the normal range.

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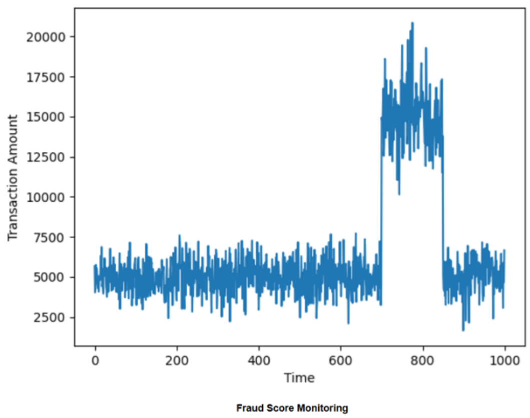

Fig. 5 Trasacton amount monitoring

The graph highlights a temporary spike in fraud risk, which may indicate abnormal behavior or concept drift in transaction patterns, triggering monitoring alerts.

- From time 0 to about 700, the fraud score remains very low (around 0.02–0.05), indicating normal and low-risk transactions.
- Between time 700 and 850, the fraud score increases sharply (around 0.30–0.60), which indicates suspicious or potentially fraudulent activity.
- After time 850, the fraud score drops back to the normal range, suggesting the system returns to normal behavior.

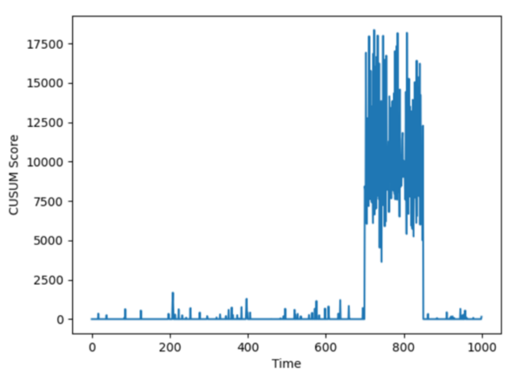

Fig. 6 Concept drift detection (CUSUM)

The graph demonstrates that the CUSUM algorithm successfully detects concept drift between time 700–850, where abnormal changes in the data pattern occur.

- From time 0 to about 700, the CUSUM score remains very low, indicating that the data pattern is stable and similar to the baseline.
- Between time 700 and 850, the CUSUM score increases sharply, showing a significant deviation from the normal data distribution.

After time 850, the score drops again, indicating that the system returns to normal data behavior.

IV. CONCLUSION

By monitoring the data and flow of the transaction we can determine the abnormality through concept drift using CUSUM algorithm. Lastly, banks need to create and employ robust AI models that can find concept drift. This is really crucial to stress. Financial data needs to be updated every time the firm evolves or new strategies to attack come up. People who run AI systems need to be able to think outside the box and adapt to new situations. This research demonstrated that an effective approach to identifying various types of drift integrates statistical approaches, ensemble learning, and real-time data processing. It is vital to realize that today's study doesn't just look for one algorithmic cure. Instead, we need a mechanism that looks at the full system, like MLOps models. This change makes it apparent that finding a change isn't the hardest part. The hardest task is making sure that the model stays correct and works on its own from start to finish. AI systems need to be able to identify problems coming and always do the right thing for them to stay accurate, reliable, and useful for things like credit scoring, finding fraud, and following the laws. These cutting-edge tools and procedures make it feasible to adapt to new situations and trust that the AI will make excellent decisions.

V. FUTURE DIRECTIONS

There are a lot of new things happening in AI and machine learning that will make it much easier to locate banks that have lost their way with concepts. These steps add to what has already been learned from the study. They also seem like fantastic approaches to develop AI systems that are more useful, clearer, and work better. Federated learning is a terrific approach to allow more people to work together on recognizing idea drift without putting the data at risk. Federated learning is a kind of machine learning that isn't all in one place. You can teach models from multiple banks or parts of a big bank to work together without needing to

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exchange confidential raw data. This has to do with privacy and security, which are two very essential topics in the corporate sector. More work is being done on federated learning algorithms that can detect and respond to idea drift in decentralized contexts. This is especially essential when the drift characteristics could be different for each person.

AI that can explain things (XAI) to make things transparent and help people trust it: Adding Explainable AI (XAI) is a huge step toward making it easier to see when ideas are changing in real time. The government watches banks closely, so it's crucial to be able to explain what the model stated would happen and why it didn't. XAI can help us figure out which qualities alter the most when things drift. This can assist us figure out why a model's behavior varies over time. To get drift, the writing ought to be easy to read. This technique of altering models is better and more useful, and politicians and other people who have an interest in the issue trust each other more.

The concept of lifelong learning, also known as incremental learning or continual learning, is to keep learning. The idea is to enable AI models keep learning from new data streams and deal with concept drift without "catastrophic forgetting," which is when fresh information causes a model forget what it already knows. Two significant features of systems for continuous learning are the flexible ensemble approach and online learning algorithms. These are approaches to handle data in a specific order. You can make AI models operate well over time without having to train them all the time by using these approaches. This is highly useful for banks because data patterns are always changing.
For this field to progress forward in the future, there needs to be a standard approach to judge things. There haven't been enough detailed benchmarks established just for banks that take into consideration the diverse sorts of data and standards that pertain to the area. This makes it hard to compare different ways in a fair way. To speed up progress and make sure that new ideas are fully and openly considered, we need to build structures like these. This will assist people who work in the field think of new things.

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