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Building on belief

AI based customer risk rating models for efficient AML compliance

Abstract

Growth in digital banking in recent years has propelled banks and financial institutions to newer heights. However, this has also been accompanied by enhanced risk of fraud and crime. Money laundering today is a sophisticated and complex activity across the globe, forcing regulators to bring in more stringent guidelines globally around anti-money laundering (AML) compliance.

Banks and financial institutions need to be more vigilant in preventing money laundering, and one way to achieve this is to ensure accurate risk rating of customers. The present system is not without its challenges – data collected is static, infrequently updated, and risk scores are not monitored and revised in real-time. Incorrect classification of risk ratings leads to repeated reviews, driving up costs and adversely impacting customer satisfaction.

Banks and financial institutions are rapidly deploying artificial intelligence (AI) algorithms as part of their analysis and decision-making process, making them a critical tool in the fight against financial crime. This white paper explores how an AI based model can analyze large volumes of data and help banks and financial institutions detect patterns in customer behavior with agility.

The intrinsic value of customer risk assessment

Money laundering has become one of the leading financial crimes across the globe. The proliferation of digital banking further expands the risk horizons for banks and financial institutions. To prevent money laundering and improve AML compliance, regulators worldwide are issuing several regulations and providing guidance to banks and financial institutions. The regulations cover all steps of the customer journey – onboarding, transaction monitoring, alert generation, investigation, and filing suspicious activity report (SAR).

As a first step in improving AML compliance, regulators expect banks and financial institutions to collect detailed information as part of the Know Your Customer (KYC) program and then carry out customer due diligence (CDD). Banks evaluate the KYC information provided by prospective customers to assess risk and arrive at risk ratings before taking appropriate onboarding decisions.

Risk rating is calculated based on certain factors such as customer occupation and industry, residential status, nationality, source of income and/or wealth, anticipated account activities, ultimate beneficial owner (UBO), whether the customer is a politically exposed person (PEP) and so on. These factors are assigned individual weightages, basis which a customer score is derived. Based on the score, customers are classified into different risk ratings such as red, amber, and green with red indicating high risk and green indicating low risk for financial institutions. Once the rating is determined, customer transactions are regularly monitored with the help of transaction monitoring rules. Risk rating has an impact on aspects such as transaction monitoring, prioritization of alerts, enhanced due diligence (EDD) for high-risk customers and frequency of review.

AI to the rescue for effective customer risk ratings

Risk rating is generated for customers during the onboarding process, and the frequency of reviews is also determined at the same time. However, there are several challenges associated with the current risk rating process – data is collected manually with pre-defined and limited parameters, and is static. In addition, customer information is infrequently updated. All this results in inadequate weightages assigned to risk factors, and inaccurate scores and classification of customers. Incorrect classification further leads to repeated reviews, driving up costs and adversely impacting customer satisfaction.

Let's consider an example of a salaried customer who is classified as green or a low-risk customer by the bank (see Figure 1). Suppose the customer changes his job within two years and moves abroad, and subsequently starts remitting money to India. Now, the underlying parameters such as place of residence, account type, and so on have changed, but the risk rating is not revised to reflect these changes, which can be flagged as non-compliance and become a cause for concern.

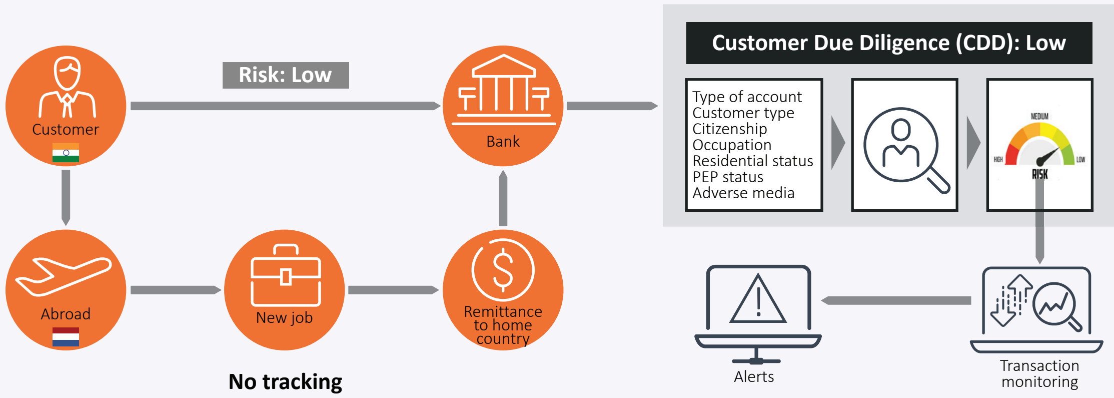

Figure 1: Initial Customer Onboarding and Change in Customer Profile After a Period of Time

Let's examine what the bank can do in this situation. To capture such changes in the customer profile, the bank can deploy an AI engine (see Figure 2) to compare the transaction patterns of the customer with the onboarding information that was used to calculate the risk rating. An AI engine can compare behavior patterns with the specific variable in the transactions and detect deviations. If there is regular deviation over a two to four-month period, the engine will update the particular variable responsible for change in behavior in the risk rating model of the bank, and subsequently update the customer's risk rating.

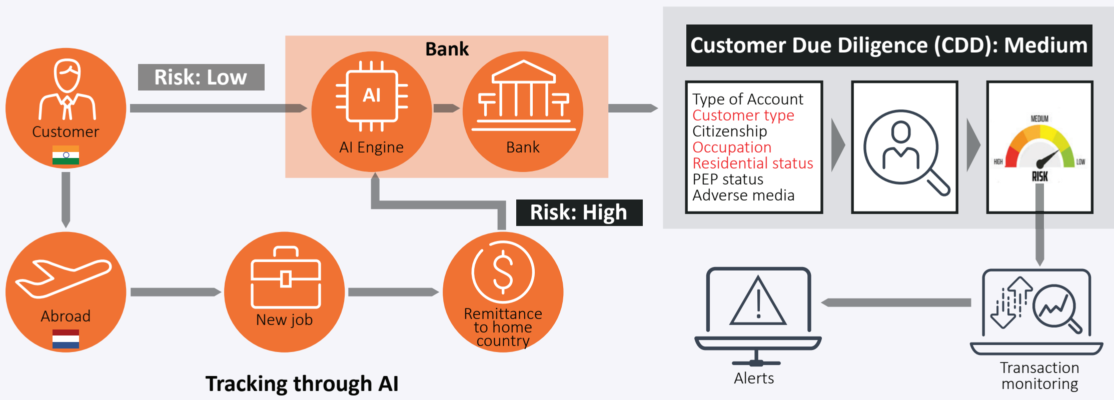

Figure 2: Use of AI for Identifying Change in Customer Profile

AI-backed risk detection model for improved customer risk rating

Enhancing fraud detection and AML compliance are key priorities for banks and financial institutions, at the same time, banks need to prevent false alerts or flagging legitimate transactions. To this end, banks must consider employing a risk detection model based on anomaly detection or outlier detection methodology to help identify the outliers or rare events that are suspicious compared with the majority of legitimate transactions. The model can be used to identify the variables or information in customer transactions that point toward deviations in customer behavior compared with the expected customer behavior based on the onboarding information available in the system. These deviations help the AI engine detect the change and update the respective variable value in the risk rating model in turn revising the customer risk rating as well. Important variables that can be identified from customer transactions include country of origin, details of counterparties, country of beneficiary, transaction amount, number of transactions, number of debit or credit transactions, date of transactions and so on. The model can be trained to learn from the input data and modify the customer's profile and behavior context. The AI engine detects meaningful patterns from rich transaction data and identifies any deviations from the existing customer profile in the system.

For instance, in the case of a salaried person, remuneration is expected to be credited into the account at the end of the month (see Figure 3). However, if the person starts his/her own business (self-employed), there will be no salary credit. The AI engine will observe this unexpected behavior and automatically update the occupation of the customer to 'self-employed' or 'other'. Similarly, the AI engine can check and update the residential status of customers based on unexpected behaviour.

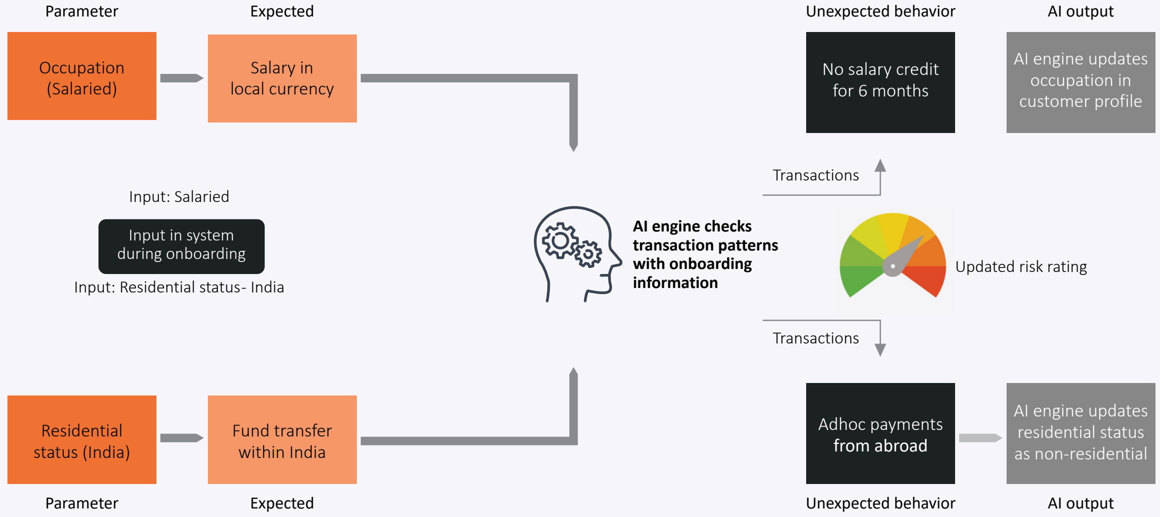

Figure 3: Use of AI for Identifying Change in Occupation and Residential Status

This risk detection model offers several advantages such as:

- Real-time change in customer risk rating enabling accurate classification of customers into risk categories.
- Enhanced due diligence for customers who moved from low to high risk.
- Accurate alert generation as appropriate transaction monitoring rules with correct threshold are applied based on updated customer risk rating.

- Improved regulatory compliance.
- Seamless alert investigations based on updated customer profiles.
- Reduction in false alerts and operational workloads.

Simply put, AI based technologies offer tremendous potential to help banks improve data collection and processing, as well as gain a single and dynamic view of customers' risk profile. A TCS-Chartis Research survey of over 100 financial institutions indicated that nearly 24% of the respondents clearly felt the need to implement AI tools for risk management.[1]

The ability of AI models to analyze data in large volumes and from several sources can help banks and financial institutions detect patterns in customer behavior with agility. Machine learning algorithms can also address data quality issues most frequently faced by banks and financial institutions. With the help of AI and ML techniques, banks can create dynamic customer risk profiles to reduce fraud, cut costs and improve customer experience.

Making the financial world safer

Prioritizing AI for risk reduction offers threefold advantage – reducing punitive costs associated with money laundering, retaining customer loyalty and improving customer satisfaction through secure systems, and leveraging automation to reduce compliance issues. Given money launderers are becoming more sophisticated, banks and financial institutions must counter them with strong measures – advanced AI based risk models are an effective addition to their arsenal. AI algorithms will continue to learn, work autonomously, and take on more complex tasks from humans, underpinned by their inherent benefits of accuracy and agility. How banks and financial institutions leverage these models to reduce risk by redefining their internal processes and addressing workforce challenges will demonstrate their ability to combat financial crime.

[1] TCS, The State of AI in Risk Management, October 2019, Accessed April 2021, https://www.tcs.com/content/dam/tcs/pdf/Industries/Banking%20and%20Financial%20Services/State-of-AI-in-Risk-Management.pdf

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