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The Future of AML

AI-Driven Predictive Analytics and Beyond

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In the ever-embryonic landscape of financial crimes and money laundering, the traditional methods of detection of ill activities and their prevention are proving insufficient. Criminals recurrently adapt, using classy techniques to launder illicit funds. To fight in this battle, financial institutions (FIs) and regulatory bodies are shifting towards the artificial intelligence (AI) and predictive analytics and equip these powerful utensils in their anti-money laundering (AML) arsenal.



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As we deep dive into the future of AML, it becomes crystal clear that AI-driven predictive analytics is an impressive game-changer. Here we will explore the transformative potential of AI in the empire of AML, shedding light on its applicability, challenges, and the macro level landscape of AML techniques and software solutions that join AI's capabilities.

Artificial Intelligence (AI) in Mitigating Money Laundering

Artificial Intelligence itself is a combination of different technologies. One of the technologies are DL (deep learning), computer vision, ML (machine learning) and (NLP) natural language processing. These subsets of AI enable machines to analyze huge chunks of data, identify patterns, and make predictions without explicit programming.

To understand this further, we mostly encounter the question at first: How does AI differ from traditional rule-based AML systems? After the efforts of many years where financial institutions have installed systems, conventional rule-based AML systems depend on predefined rules and thresholds to flag suspicious transactions. While these systems are reliable to a certain extent, they struggle with the distinction and complex nature of modern financial transactions. AI, on the other hand, learns from historical data that allows to understand the pattern or behavior which helps in evolving money laundering techniques. It outshines in identifying subtle, previously unknown patterns indicative of illicit activities.

Benefits of AI in AML

Some of the benefits which have been witnessed after the introduction of AI in financial system are as follows:

- i. **Enhanced Accuracy and Efficiency:** The algorithms embedded in AI tools can analyze massive datasets with much precision, reducing false positives and negatives in AML alerts. It enables automation of routine tasks, such as transaction monitoring and frees up human resources for more complex investigations.
- ii. **Real-time Detection:** Solutions equipped with AI can provide real-time alerts, enabling proactive measures to be taken on real time basis on suspicious activities which are accurately identified.
- iii. **Adaptability:** In earlier days AI was not trained sophisticatedly. These models evolve over time, continuously improving their ability to detect new money laundering methods.
- iv. **Transaction Monitoring:** AI-powered transaction monitoring systems analyze customer transactions in real-time. They consider multiple factors, not limited to transaction history, customer profiles, and external data sources, to identify potentially suspicious activities. AI-based system detects unusual transaction patterns for a customer who typically makes small purchases but suddenly initiates several large international wire transfers.

- v. **Customer Risk Assessment:** AI also contributes in assessing the risk associated with each customer. By examining data related to customers' financial behavior, AI can categorize them into low, medium, or high-risk groups. An AI model may flag a customer as high-risk if it discovers that they frequently conduct transactions with the entities in countries known for high money laundering risk or are in any financial sanctions list.
- vi. **Enhanced Due Diligence:** By using tools that are AI-driven, due diligence processes can speed up customer onboarding by automating document verification, background checks, and beneficial owner identification. A KYC (Know Your Customer) system which is equipped by AI can enable financial systems to quickly verify the authenticity of identity documents and cross-reference them with watch-lists available.
- vii. **Anomaly Detection:** Tools equipped with AI can identify unusual patterns or outliers in transaction data, helping investigators pinpoint potentially suspicious activities that may go unnoticed by traditional methods. It detects a sudden surge in cash deposits at an ATM, suggesting potential structuring of deposits to evade reporting requirements.
- viii. **Regulatory Reporting:** Usage of AI streamlines the process of generating and filing Suspicious Activity Reports (SARs) by automating the identification and documentation of suspicious activities. If proficiently used, an AI system can compile a comprehensive STR report by aggregating relevant transaction details, customer information, and contextual data.
- ix. **Fraud Detection:** AI also contributes to fraud detection by identifying fraudulent activities, such as account takeovers (buying of KYCs/hacking) and phishing scams. AI helps in detection of a series of login attempts from different geographical locations within a short time frame, indicating a potential account takeover attempt.

Practical Examples from Across the Globe

The financial sector, including banks, credit unions, payment processors, and regulatory bodies have accepted the use of AI to facilitate their customers more elegantly and quickly. Some of the user cases are defined below on how AI is currently being utilized globally in the financial sector.

- i. **HSBC:** One of the world's largest banks implemented an AI-driven AML system to enhance transaction monitoring. This execution resulted in a significant reduction in false positives, allowing investigators to focus on genuinely suspicious activities.
- ii. **FinCEN:** Financial regulator 'The Financial Crimes Enforcement Network' (FinCEN) in the United States employs AI algorithms to analyze suspicious activity reports (SARs) and identify emerging trends in

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money laundering. This data-driven approach aids in shaping regulatory policies and priorities.

- iii. **Danske Bank:** In response to a major money laundering scandal, Danske Bank applied AI-powered solutions to their systems to strengthen its AML framework. AI is used for transaction monitoring, customer due diligence, and risk assessment.

Predictive Analytics in AML: A Transformative Approach to Detecting Financial Crimes

To negate money laundering, staying ahead of money launderers is a constant challenge. Conventional anti-money laundering (AML) methods, usually depend on the systems that are rule-based, which are not capable of capturing the ever-changing maneuvers employed by illegitimate actors. Entering into the predictive analytics, a powerful tool that binds the potential of machine learning and artificial intelligence (AI) to transform AML efforts, can identify the maneuvers by the money launderers.

Predictive analytics is a data-driven AI method that stimulates historical data to make informed forecasts about future events. In case of AML processes, predictive analytics involves the use of advanced algorithms and statistical models to identify patterns, anomalies, and potential money laundering activities. Unlike rule-based systems which mostly rely on predefined criteria, predictive analytics can adapt and transform, making it predominantly effective in detecting new and sophisticated money laundering schemes.

Predictive Modeling Adoption

Predictive models are architected to analyze vast amounts of customer profiles, transaction data and other relevant information to make forecasts about the likelihood of a transaction or customer being involved in illegitimate activities. Now we will try to understand how predictive modeling works in AML.

- i. **Data Collection and Preprocessing:** Predictive models start by collecting and preprocessing data from various sources. This includes transaction

records, customer information, historical AML alerts, and external data such as news articles and regulatory updates.

- ii. **Feature Engineering:** In this step, data scientists identify relevant features or variables that could be indicative of suspicious activities. These features can include transaction amounts, frequency, geographic locations, customer behavior, and more.
- iii. **Model Training:** Once the data has started to gather, predictive models are trained using historical data. During this type of exercise, the model learns to recognize patterns and relationships in the data that are linked with money laundering.
- iv. **Prediction and Scoring:** After performing training to a certain extent, the model is ready to make predictions. When a new transaction or customer profile is entered into the system, the model assigns a score or possibility indicating the likelihood of it being involved in money laundering. Higher scores suggest a higher risk level.
- v. **Machine Learning Algorithms for AML:** Predictive analytics in AML relies on a range of machine learning algorithms. These algorithms are designed to identify complex patterns and correlations within the data. Some popular machine learning algorithms used in AML are mentioned below.
 - **Random Forest:** This ensemble learning algorithm combines the predictions of multiple decision trees to improve accuracy and reduce overfitting. It is particularly useful for handling large and complex datasets in AML.
 - **Gradient Boosting:** Gradient boosting algorithms like XGBoost and LightGBM are known for their high predictive accuracy. They are often used to uncover delicate patterns in AML data.
 - **Neural Networks:** Deep learning models, including artificial neural networks, outshine at dispensation unstructured data such as text and images. In AML tools, they are used for tasks like analyzing transaction narratives and news articles (adverse media) for potential money laundering indicators.

Benefits and Challenges of Predictive Analytics in AML

Predictive analytics offers several advantages in the fight against money laundering. Some of them are defined below.

- i. **Enhanced Accuracy and Efficiency:** Predictive models can analyze massive datasets with precision, reducing both false positives and false negatives in AML alerts. This leads to more effective use of investigative resources. Automation of routine tasks, such as transaction monitoring and risk assessment, frees up human investigators to focus on complex cases that require expert judgment.
- ii. **Real-time Detection:** Predictive analytics can provide real-time alerts, allowing financial institutions to take immediate action when suspicious activities are identified.
- iii. **Adaptability:** Predictive models continuously evolve as they learn from new data. This adaptability is crucial in detecting emerging money laundering tactics.

However, implementing predictive analytics in AML is not without its challenges and some are also itemized below.

- i. **Data Quality:** Predictive models heavily rely on data quality and consistency. Inaccurate or incomplete data can lead to unreliable predictions and can be volatile as it allows wrong decision making at analyst level.
- ii. **Model Interpretability:** Understanding why a model makes a specific prediction can be challenging. It requires proper understanding of system alerts and indicators. Model interpretability is essential, especially in regulatory environments where explanations for decisions are required.
- iii. **Bias Mitigation:** Predictive models can inadvertently inherit biases present in historical data. Since all patterns are suspicious, but not for ill purposes, it can deceive the analyst. Efforts must be made to identify and mitigate these biases to ensure fairness.

Natural Language Processing (NLP) in AML

Money launderers often leave digital footprints in the form of text data, whether it is in transaction narratives, emails, or news articles (adverse media). Natural Language Processing (NLP), a subdivision of AI, stresses on the collaboration between humans and machines using natural language. In the territory of AML, NLP has proven to be invaluable in the following ways:

- i. **Analyzing Unstructured Data:** Most of the data relevant to AML investigations is unstructured, such as adverse media reporting on financial crimes. NLP algorithms can scrutinize through vast amounts of text data to identify keywords, phrases, and sentiment that may indicate money

laundering activities. An NLP model can detect references to suspicious financial transactions or individuals involved in financial wrongdoing in media reports.

- ii. **Monitoring Communication:** NLP can be deployed to have surveillance on internal and external communications for red flags. This comprises analyzing emails, chat logs, and other forms of written communication within an organization to identify potentially illicit discussions or transactions e.g., detecting discussions about evading AML controls or using coded language in emails.
- iii. **Enhancing KYC Processes:** NLP can also assist AML processes in automating Know Your Customer (KYC) and due diligence steps by extracting relevant information from customer documents and verifying their authenticity. For example, automatically extracting and verifying identity information from scanned ID cards, passports and driver's licenses.

Network Analysis and Graph Theory

Money laundering is rarely a solo effort; it is frequently conducted by the complex networks of individuals and entities. Network analysis and graph theory, both rooted in advanced mathematics and AI, enable AML analysts to visualize and analyze these complicated connections. Some of the key functions are elaborated below.

- i. **Analyzing Complex Money Laundering Networks:** By representing relationships between individuals, accounts, and transactions as nodes and edges in a graph, AML analysts can identify key nodes (entities) that play pivotal roles in money laundering schemes. For instance, detecting that a particular individual is connected to multiple accounts involved in suspicious transactions, indicating their centrality in the network.
- ii. **Visualizing Data:** Graph-based representations allow for spontaneous visualization of relationships, making it easier for AML specialists to comprehend the structure of money laundering networks. For instance, creating network visualizations that show the flow of funds between accounts and individuals.
- iii. **Identifying Anomalies:** Graph theory can be used to detect irregularities or unusual patterns within networks, potentially exposing hidden money laundering activities. For instance identifying clusters of accounts that frequently exchange funds in a circular manner, a common money laundering tactic.

Emerging Technologies in AML

Since technology is in constant evolution, and rapid advancing technologies are finding their way into AML practices. Some of them are defined below.

- i. **Blockchain:** While often associated with cryptocurrencies, blockchain technology

also has applicability in AML processes as well. Blockchain's transparent and immutable nature can assist in tracing the flow of funds and identifying suspicious transactions like analyzing the blockchain ledger to track the movement of cryptocurrencies involved in money laundering.

- ii. **Internet of Things (IoT):** IoT devices produce vast volumes of data, which, when analyzed with AI, can provide valuable insights for AML efforts. Such as detecting unusual patterns in sensor data from IoT devices in a manufacturing facility that may indicate illicit activities.
- iii. **Quantum Computing:** Although still in its early stages, quantum computing provides exponentially faster data analysis. In AML, this could mean near-real time analysis of vast datasets, such as analyzing years' worth of financial transaction data in a matter of seconds to identify patterns indicative of money laundering.

While emerging technologies fight against money laundering, they also have challenges. Safeguarding the privacy and security of data, addressing ethical concerns, and staying up to date with swiftly evolving technologies are some of the steeplechases that organizations must navigate to fight against money laundering.

Challenges and Ethical Considerations in Leveraging AI For Anti-money Laundering (AML)

As FIs and regulatory bodies advance towards artificial intelligence (AI) to strengthen their AML efforts, they must face the challenges of a host of trials and ethical considerations. While AI holds tremendous potential in the fight against money laundering, it also raises complex issues that demand careful consideration. Some of them are listed below.

- i. **Data Privacy and Security** A key challenge in using AI for AML is ensuring the privacy of individuals whose data is analyzed. AML systems require access to sensitive financial and personal information, and protecting this data from unauthorized access or breaches is paramount. For instance, AML algorithms may unintentionally expose the financial details of innocent individuals if not designed with robust privacy measures. Safeguarding the data used by AI models is essential. Financial institutions must implement strong encryptions to their customers' data, access controls within the organization and cybersecurity measures to protect against data breaches. For instance, unauthorized access to transaction data or customer profiles can lead to privacy violations and data leaks.
- ii. **Biases and Fairness** AI models can inherit biases present in historical data as they are gathered on the certain sandbox style selected data. If not addressed, these biases can result in unfair or discriminatory outcomes in AML decisions e.g.,

AML algorithms may disproportionately flag individuals from certain demographics, leading to unjust scrutiny.

Ensuring fairness in AML practices is crucial. An AI system that flags transactions from specific regions as suspicious due to historical patterns may inadvertently propagate geographic bias.

- iii. **Regulatory Compliance** AML regulations are subject to frequent changes and updates. Staying compliant with these evolving regulations while implementing AI systems can be a challenging task for the Compliance and AML personnel. For instance, AML systems must adapt to new regulatory requirements, such as enhanced due diligence measures for specific customer segments.

Regulators often require that AML decisions be explainable with facts and be transparent. Ensuring AI models are interpretable can be difficult, especially for complex deep learning algorithms. For example, regulators may request an explanation for why a specific transaction was flagged as suspicious, which can be challenging with black-box models.

- iv. **Model Validation and Accuracy** The accuracy of AI models depends on the quality and quantity of the data used for training. Incomplete or erroneous data can lead to inaccurate predictions. For instance, inaccurate transaction data may result in false positives or missed detections of money laundering activities.

Ensuring the trustworthiness of AI models is crucial. Validation processes must be rigorous to prevent false positives that can overwhelm investigators or false negatives that may lead to money laundering going undetected. If model validation is not executed, it may generate numerous false alerts, straining investigative resource and effect their work quality too.

- v. **Transparency and Elaborating Ability** Understanding how AI models arrive at their decisions can be a challenging task for the handlers, especially with complex deep learning models. Lack of transparency can lead to skepticism and mistrust. Financial institutions may become vulnerable to adopt AI systems that they cannot understand or explain to regulators.

AML decisions often require descriptions for regulatory compliance and customer communication. Ensuring that AI models can provide meaningful explanations is crucial. For instance, regulators may request detailed explanations for why a specific customer's transaction was flagged as suspicious.

- vi. **Ethics in Investigations** AML investigations must respect the presumption of innocence. Algorithms should not unfairly label individuals as criminals without having strong evidence. Automatically freezing assets or reporting individuals as



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suspicious, based solely on algorithmic alerts, can harm innocent parties and leads to discomfort from the customers.

Balancing AI automation with human oversight is essential. Human experts should play a crucial role in reviewing and interpreting AI-generated alerts. AML investigators may need to review AI-generated alerts and make final determinations about their validity as they are the ones who make decisions at the end.

The Road Ahead: AI-powered AML Strategies Transforming the Fight Against Money Laundering

The road ahead for AML is marked by AI-powered strategies that promise to revolutionize how we detect and prevent financial crimes.

As technology advances, predictive analytics will continue to evolve, becoming more accurate and efficient. Machine learning models will polish their ability to detect even subtle patterns indicative of money laundering, reducing false positives and improving the effectiveness of AML programs. Predictive models will integrate more contextual data, such as transaction history and customer behavior to make more informed estimates.

Addressing the challenge of model interpretability, AI researchers and developers will focus on creating models that are more transparent and can provide

detailed explanations for their decisions. This will enhance trust in the systems and regulatory compliance. Explainable AI models will be able to provide clear rationales for flagging specific transactions or customers.

AI-powered AML systems will increasingly operate in real-time, allowing for immediate detection and response to suspicious activities. This will enable financial institutions to proactively prevent money laundering before it occurs. Real-time monitoring will enable instant alerts for transactions that deviate from normal behavior, preventing illicit funds from being moved.

In conclusion, the future of anti-money laundering (AML) efforts lies in the transformative power of artificial intelligence (AI), predictive analytics, and emerging technologies. As financial crimes become increasingly sophisticated, traditional rule-based systems are proving inadequate. However, AI-driven predictive analytics offer enhanced accuracy, efficiency, and adaptability in detecting illicit activities.

Moreover, as we are still in the initial phase of adopting Artificial Intelligence in our businesses and financial sector, it requires huge efforts in terms of finances and computing equipment which still creates a friction in seamless adoption of the technology. Besides adopting AI, we need to espouse more sophisticated techniques to convert in AI within the available systems to make it much more effective and affordable.