WHITE PAPER

LEVERAGING ARTIFICIAL INTELLIGENCE & MACHINE LEARNING IN CREDIT RISK MANAGEMENT

Navigate your next

Overview

In recent times, the traditional Credit Risk Management (CRM) function of financial institutions (FIs) has been under intense pressure to deal with the seemingly insurmountable external and internal forces. Couple of key contributors to such external forces are **increased regulations** and the **foray of established technology companies and new FinTechs** that are disrupting the FIs' traditional credit lending market.

Today, regulators expect FIs to take a more proactive approach in dealing with credit risk. For example, IFRS9 standards[1] have specified that FIs regularly review the methodology and assumptions for estimating their expected credit losses. In addition, it is expected as a part of regulations such as Basel IV[2] for FIs to reduce their over-reliance on external credit rating agencies for credit and counterparty risk management.

Pure technology companies and new FinTechs are now venturing into the lending business with new age technology capabilities. For e.g., Google, Amazon, Facebook and Apple in developed markets and Baidu, Alibaba and Tencent in Chinese markets are leveraging big data and other new-age technology capabilities such as Artificial Intelligence (AI) and Machine Learning (ML). This is being done in order to simplify their credit lending decisions and effectively manage their credit risk; and in turn capture significant portion of traditional FIs lending businesses.

Internal pressure to FIs' credit risk function arises from the **growing customer expectations** for a streamlined and hassle-free credit lending mechanism, and the **demand from business** to increase profit and keep a check on the non-performing assets.

Customers are aggrieved that their FIs' traditional credit lending systems and processes take substantial time to assess their credit risk and make the lending decisions. While FIs have adopted many new non-traditional digital channels, processes and credit products; their CRM function has remained inefficient. Additionally, for customers with little or no credit history, it is a challenge for FIs to assess their credit risk and to decide the optimum pricing for such customers.

FIs have also been grappling with the tug-of-war between their CRM and the sales functions. While the FIs' CRM function remain focused on keeping a check on the credit losses, the sales function on the other hand is primarily focused on increasing revenue and tapping into new customer segments. Alas, FIs' existing CRM systems are unable to provide an optimal solution for these two divergent goals.

To overcome the aforementioned challenges, it has now become imperative for FIs to transform their CRM function and leverage new-age technologies such as AI and ML.

As per Deloitte Global Risk Management Survey 2018[3], 19% and 25% of the respondents stated that their firm has been using cognitive analytics and ML respectively for risk management. Respondents also highlighted that these emerging technologies would help increase operational efficiency and reduce error rates (68%), enhance risk analysis and detection (67%), enhance timely reporting (60%), improve the scope and coverage of risk management (via exception handling vs. sample testing) (60%) and reduce costs (45%).

Clearly then, there is significant enthusiasm and appreciation from the market towards leveraging AI/ML based solutions in firms' risk management functions.

Use Cases for effective CRM using AI/ML across the credit lending value chain

Value Chain Stage	AI/ML Use Case	Value Proposition
Origination	**Pre-qualification:** Pre-qualifying the customers for loan products based on 3rd party / alternate data, such as: a) occupation (salaried/self-employed); b) income related data (indicative from other data sources if not directly available); c) address data (profiling locality from open source real-estate websites) E.g.: Project Blue Sky by Yes Bank[4]	• Can help pre-qualify thin-file customers (i.e. customers with limited data with the FI and the credit bureau)
	Loan application and processing: • AI/ML can help automatically classify the documents that the borrower has submitted and alert the documents collection team in case of discrepancies • Natural Language Processing (NLP) powered chatbots can aid contextual conversations with customers - based on the customer's profile and the product applied for • AI/ML based virtual advisors that understand customers queries and instantly provide well-informed responses • Support automatic extraction of relevant details from the documents using Optical Character Recognition (OCR) and Intelligent Character Recognition (ICR) E.g.: RHB Bank has implemented chatbots in the initial stage of loan application to make it easier and to ensure completeness of the application[5]	• Ensures an optimized and complete document collection process • Streamlined and expedited loan application and processing • Less handoffs in the document submission process • Factors that may strongly impact the risk rating but has not been directly declared by the customer in the application, can be automatically extracted from the documents
Underwriting	**Credit scoring and decision:** • In addition to structured data (such as transaction and payment history), ML and NLP capabilities can leverage real-time intelligence from various other external and internal unstructured/semi-structured data sources (such as credit bureaus, social media activity, mobile phone usage, text message activity, spending behavior, 3rd party data providers etc.) to enable segmented creditworthiness assessment and precise credit risk scores • Leverage various alternative data sources to assess the willingness and ability to repay and thereby generate credit scores for potentially creditworthy borrowers, for whom credit scores cannot be otherwise generated through traditional methods. As such potential borrower lack sufficient historical credit information to be "scorable" E.g.: Companies such as ZestFinance and Experian are implementing AI powered underwriting solutions on alternate data sources to assess borrowers' lending ability[6]	• Reduced credit lending risk • Enhancements in the level of credit access
	Loan pricing: ML based optimization algorithms can help FIs arrive at optimal loan pricing for a customer – by assessing multiple dimensions such as: a) customer attributes, b) products offered, c) competitiveness in the market, d) credit limits, e) ROI hurdles, f) business targets and budgets E.g.: Lending Club prices the loan at the time of application[7]	• Enhanced profitability • Enhanced customer satisfaction

Value Chain Stage	AI/ML Use Case	Value Proposition
Loan Administration/ Management & Reporting	**Macro credit risk and revenue assessment & modeling:** • Leverage ML based support vector machines to model and assess credit risk and revenue, and precisely predict potential scenarios • Apply generalized classification and regression trees (CART) to a very large dataset to build credit risk models • Leverage traditional credit factors such as debt-to-income ratios, and make use of vast amounts of internal & external data, to assess many other factors such as transactional data, liquidity ratio, loan/trade credit payment behavior, social media data, geographical information, consumer data etc E.g.: Experian has developed risk and revenue assessment systems for lending decisions[8]	• Improved credit risk and revenue assessment
	Credit default prediction: • ML backed credit default prediction models that can enable more accurate and instant credit decisions • Solution can automatically use much broader range of data sources - including business networks and news • Solution's algorithms can also be leveraged to improve Early Warning Systems (EWS) and for providing mitigation recommendations, based upon the previous responses E.g.: ING's EWS system analyzes multiple sources, predicts the credit risk of customers, and helps in taking proactive actions to prevent losses[9]	• Significant reduction in credit losses
	Issue identification and action recommendation: • Aid in tracking of performance at an account and portfolio level and create early warning systems for proactive decision making • ML based self-learning algorithms to predict the risks based on various factors, which affect the risk of the portfolio • Fed with historic data on how specific risks were mitigated, ML algorithms can prompt the risk analysts about actions that are recommended for predicted risks	• Predict credit risks proactively • Modify business strategy on-the-go to align with the target financial results • Enable streamlined and fast-tracked decision-making process and emulation of best practices for issue resolution
	Sophisticated reporting: By leveraging ML backed robotic and cognitive automation capabilities	• Proactive and highly insightful reporting

Exhibit 1: *AI/ML use cases for effective CRM*

Adopting AI/ML in CRM: Key Considerations

For AI/ML adoption within their CRM function, FIs should take an end-to-end approach – one in which the AI/ML capabilities are entrenched across all of the phases of a customer's journey (right from the acquisition stage).

Data Architecture – Need to be flexible and scalable with capability to ingest high volume and velocity of data

Determine Acquisition Risk	Manage Exposure	Track Performance	Collections Risk Management	Portfolio Management

Exhibit 2: *Key considerations for enabling AI/ML based CRM solution*

- **Data architecture:** FIs need to take a long-term view vis-à-vis their CRM data architecture. Towards this, they should consider implementing a flexible data layer that can scale-up as needed. Afterall, the AI/ML based CRM solution that the FI plans to implement should be able to seamlessly ingest all of the required data – including the unstructured ones. Additionally, FIs need to institute robust data governance mechanism and tools.

It is desirable that the FIs' data architecture possess the following capabilities:

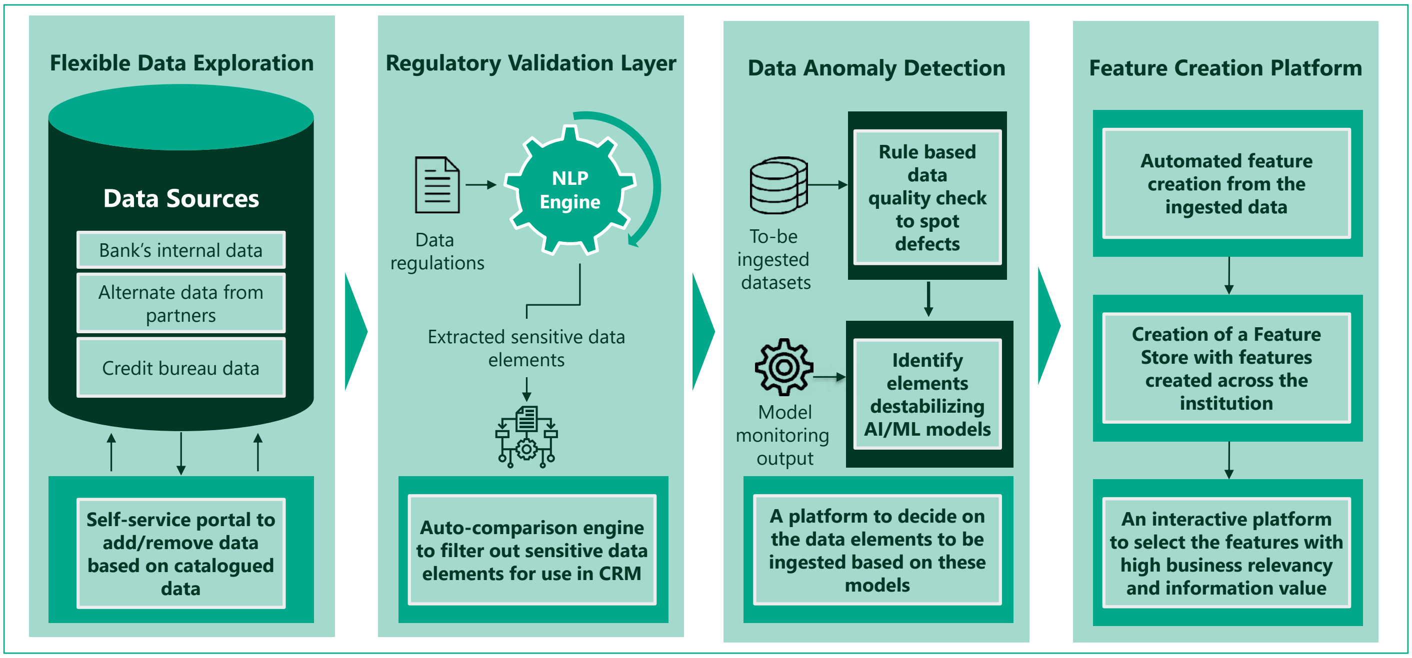


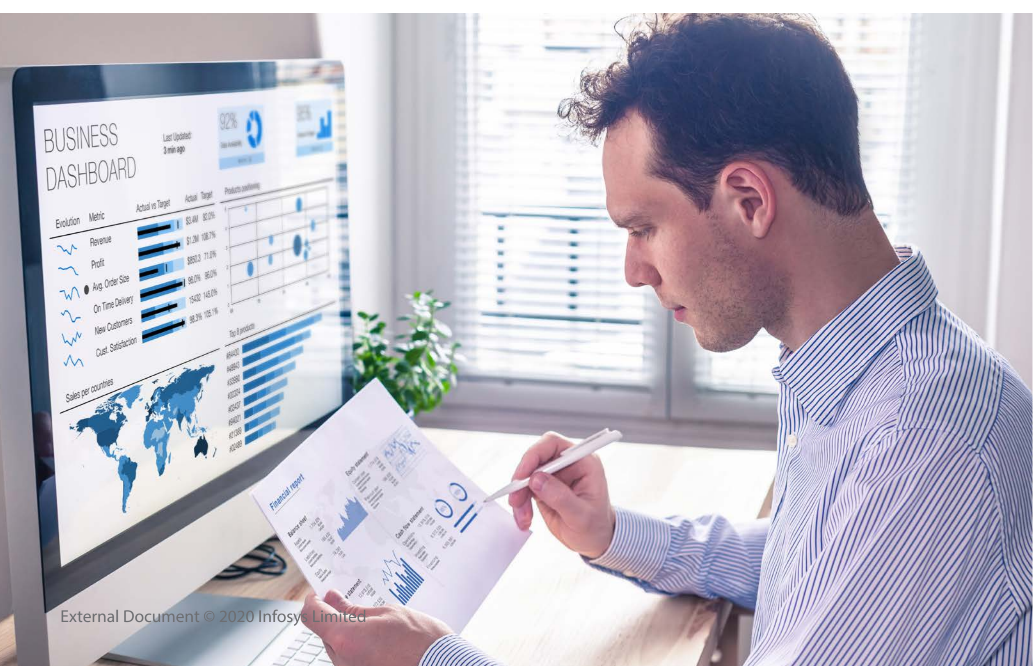
Exhibit 3: *CRM solution data architecture components*

1. **Flexible data exploration:** Over and above the traditional data sources, solution should be able to leverage alternate data such as customer spending behavior, utility bill payments, rental payments, savings and investment pattern etc. in the credit risk models. Further, using a combination of AI and rule-based algorithms, the system should be able to automatically catalogue the data into various categories - domain, quality level, lineage, source etc. Consequently, this would allow the ML algorithms to find cross-domain relationships across datasets. Additionally, visual representation of the data cataloguing and domain relationships is desirable.

2. **Regulatory validations:** Solution should be able to automatically recognize and catalog the data elements that are potentially sensitive – vis-à-vis privacy and other compliance mandates. Towards this, solution's robust NLP capability should be extensively leveraged to extract sensitive data elements from regulatory and other concerned documents. Post such validations, the data elements that are not sensitive can be ingested into the CRM models.

3. **Data anomaly detection:** The data being considered should be passed through an ML based anomaly detection layer – that can potentially spot and react to data defects. Defects can be with respect to attributes such as data completeness, outliers, nonstandard data and various other data quality issues. Care should be taken to ensure that there is no overfitting of data, which destabilizes the models, and introduces bias. Also, enabling a feedback loop from the model-monitoring platform into the anomaly detection layer is recommended.

4. **Feature creation platform:** An easy to use interactive platform can be provided to combine data elements and create relevant features for considering in the models. Companies like Alteryx are addressing this by applying Deep Feature Synthesis[10] to extract predictive features from a dataset. Feature Store could also be implemented that would house all the features for future reference. Further, an automated feature selection mechanism can be implemented to explore the features in the store and identify relevant ones for the CRM purpose.



- **CRM at individual customer level:** FIs' AI/ML based CRM solution should be able to look beyond the traditional CRM approach of evaluating creditworthiness of a new customer solely based on conventional information such as occupation, customer type, credit bureau scores etc. Instead, the solution should be able to thoroughly consider the following aspects – both at the time of onboarding and on ongoing basis – as relevant.

Determine Acquisition Risk		Manage Exposure		Track Performance		Collections Risk Management	
Customer micro-segmentation	Build ML based acquisition scorecard	ML based loan pricing optimization	Auto-assessment of systemic and reputation risk	Build automated EWS	ML based risk simulator to track EWS	Customer segmentation	Early identification of self-cure & non-self-cure customers using ML

***Exhibit 4:** Key CRM considerations at customer level risk*

1. **Determine acquisition risk:** Before assessing the risk of a new customer, FI should focus on creating homogeneous groups of customers with similar demographic attributes and behavioral pattern from an ability to pay back perspective. Towards this, the solution should utilize a blend of ML techniques such as clustering and decision tree to analyze the loss experience by key attributes of the customer. A multivariate approach can be followed to create sharper customer risk profiles and identify customer segments with similar characteristics.

   Further, the developed customer risk profiles, and the past performance (vis-à-vis various financial transactions), should be leveraged to develop predictive risk models and enable risk scores that capture the acquisition risk of the given customer. The acquisition risk scorecard can be prepared using classification methods such as logistic regression, decision trees, neural networks, or an ensemble.

2. **Manage exposure:** FIs' AI/ML based CRM solution should be capable of leveraging an overlay of risk factors on the credit product recommendation model for customer. Solution should be capable of understanding and identifying the inherent products risk, and the ones which should be automatically factored in while recommending a particular credit product to a customer.

   Further, once the solution has determined the product to be offered, it should leverage a robust AI/ML based risk-based pricing and optimization model to arrive at the optimal product pricing aspects (credit line, collateral value, interest rate) for a given customer. To devise a risk averse pricing strategy, the solution should take into consideration outputs from various other models such as price sensitivity, loan-to-value, propensity to churn etc.

3. **Track performance:** FIs should leverage AI/ML capabilities to enables early warning system (EWS) to proactively and timely predict credit default. Refer exhibit 5 for the key CRM performance tracking components.

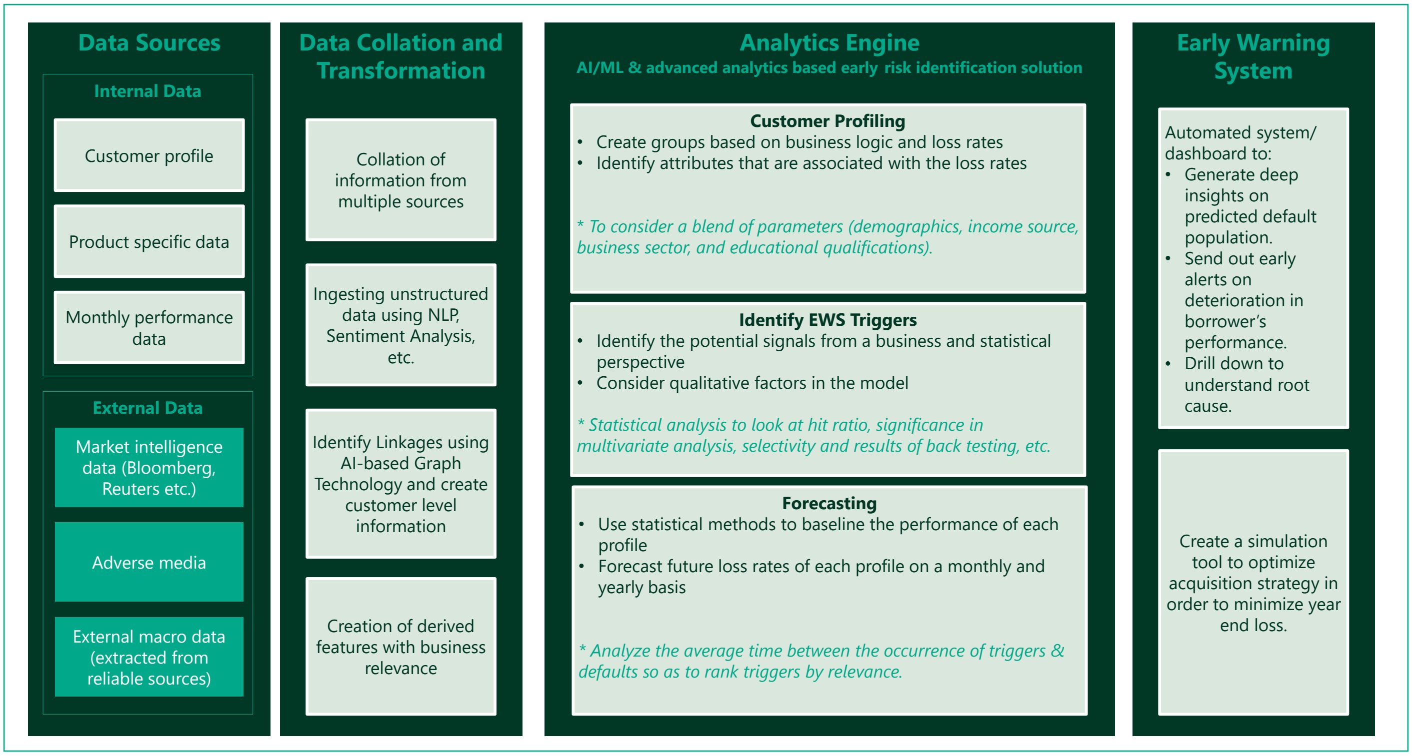


Exhibit 5: *CRM performance tracking components*

4. Collections risk management: FIs should work towards implementing AI/ML based next-gen collections management system. Such a system should enable: a) ML based customer segmentation b) early identification of self-cure and non-self-cure customers.

Using such a system, FIs will be able to classify customers into microsegments, thereby enabling more targeted recovery interventions. For example, if a customer is identified as a regular-forgetter, collections efforts can be minimal such as sending him a text message. For other segments that have more severe ramification, more detailed intervention would be needed. Further the ML based system would help classify customers as self-cure and non-self-cure customers. FIs can then invest additional collections effort on such non-self-cure customers as predicted by the system. This approach would help FIs achieve higher rate of recovery from their riskier customers.

- **CRM at loan portfolio level:** In addition to proactively assessing and tracking the credit risk at each individual loan level, system should also be able to proactively track and manage the credit risk at a loan portfolio level. Towards this, FIs' AI/ML based solution should automatically consider credit risk rating change, historic default and loss experience of FI's own credit portfolio, credit market data from the rating agencies, market observed credit spread data and other relevant internal and external structured and unstructured data.

It is recommended that FIs enable an interactive model designing platform that can utilize the abovementioned data to understand the portfolio level credit issues. Refer exhibit 6 for the key CRM considerations at portfolio level.

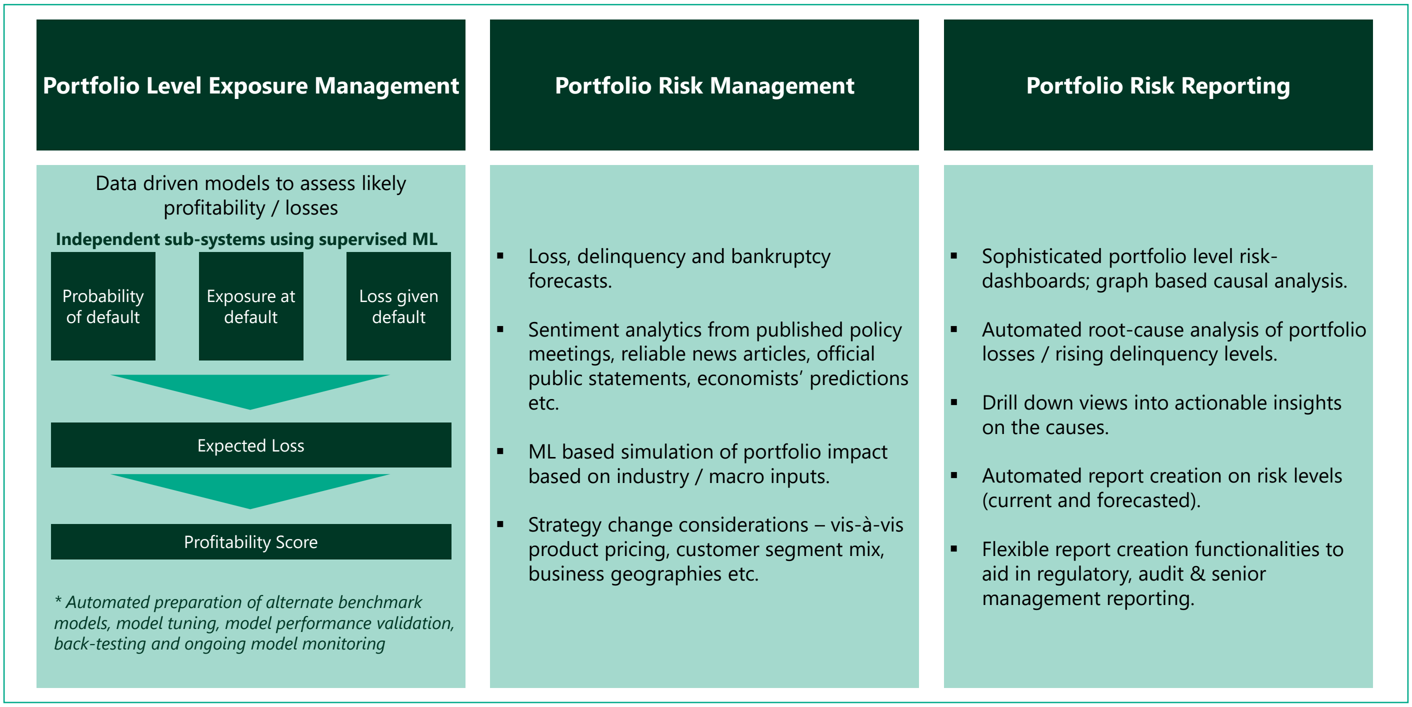


Exhibit 6: *CRM portfolio management considerations*

Conclusion

AI and ML technologies can play a key role in improving the CRM function for an FI. Hence, FIs should actively consider leveraging these new-age technologies, and importantly adopt a strategic and phased approach towards its implementation. Those that do would reap immense benefits.

For example, subprime auto lender "Prestige Financial Services", in partnership with ZestFinance (a leading AI company) implemented the industry's first fully explainable ML model to predict borrower risk. The solution has helped Prestige in achieving 36% rise in new applicants resulting in a 14% more approval rate. Within six months of implementing the AI-based credit underwriting model, Prestige was able to double its lending volume without added portfolio risk.[11]

About the Authors

Anjani Kumar

Principal Consultant, Risk and Compliance Practice, Financial Services Domain Consulting Group, Infosys Limited.

Anjani has over 20 years of comprehensive IT, domain and process consulting experience. Currently, he manages several strategic initiatives including the Competency Development Program and Thought Leadership showcasing efforts. Over the years, he has provided consulting services and managed many large and critical IT engagements for numerous key clients. He was also recognized as the lead process auditor for the IT division of a major global bank. He has extensive techno-functional skills and an in-depth understanding of quality and process models – CMMI, Six Sigma, ITIL, etc.

He can be contacted at anjani_kumar@infosys.com

Pratik Das

Senior Consultant, Risk and Compliance Practice, Financial Services Domain Consulting Group, Infosys Limited.

Pratik has over 6 years of experience ranging from driving projects for operation effectiveness to designing solutions in the Risk and Compliance space for FIs. He possesses rich domain knowledge in Anti Money Laundering, Fraud Management and Anti Bribery and Corruption. He has completed ICA Advanced Certificate in Anti Money Laundering and AML KYC certification by IIBF.

He has successfully led major programs such as false positive reduction for client screening systems and automation of screening investigation in one of the leading financial institutions in UK. Currently he is working as a Business Analyst with a UK banking major for implementing Actimize related projects for Trading and Investment products.

He can be reached at pratik.das@infosys.com

References

1. https://www.nbg.gov.ge/uploads/fsc/ifrs/impairment_guidlines_ifrs_9_nbg.pdf
2. https://www.bis.org/bcbs/publ/d307.pdf
3. https://www2.deloitte.com/content/dam/insights/us/articles/4222_Global-risk-management-survey/DI_global-risk-management-survey.pdf
4. https://economictimes.indiatimes.com/industry/banking/finance/banking/personal-loans-simplified-all-that-matters-part-2/articleshow/70604822.cms?from=mdr
5. https://www.computerweekly.com/news/450427104/RHB-Bank-rolls-out-chatbot-for-loan-applications
6. http://www.experian.com/business-services/customer-risk-assessment.html

   https://www.zest.ai/blog/zaml-fair-our-new-ai-to-reduce-bias-in-lending
7. https://www.fdic.gov/bank/analytical/cfr/bank-research-conference/annual-17th/papers/14-jagtiani.pdf
8. https://www.experian.com/business-services/customer-risk-assessment.html
9. https://hollandfintech.com/2019/01/ing-develops-early-warning-system-for-credit-risk/
10. https://blog.featurelabs.com/deep-feature-synthesis/
11. https://www.zest.ai/press/prestige-financial-services
12. McKinsey on Payments - Special Edition on Advanced Analytics in Banking
13. https://www.bis.org/ifc/publ/ifcb50.htm

For more information, contact askus@infosys.com

Infosys
Navigate your next