

The Role Of Big Data Analytics And Artificial Intelligence In Modern Banking: A Multi-Applications Analysis

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Abstract—To be competitive in a time of fast digital transformation, banks have to welcome developing technologies—especially artificial intelligence (AI) and big data analytics (BDA). National and international banks all over are working to develop their offerings to keep clients, draw new business, and boost profits. Still, artificial intelligence applications in banking largely consist in chatbots or back-office process automation. With an eye toward commercial banks especially, this article investigates the larger prospects and useful applications of artificial intelligence and BDA in the banking industry. It seeks to give a thorough summary of current scholarly work and point up untapped prospects for next study. Although there are many use applications, the paper focuses on important topics including fraud detection, loan default prediction, credit scoring, and tailored marketing. Apart from evaluating developments in data preprocessing methods and machine learning approaches, this work especially addresses the influence of dataset size on model performance. This helps to design stronger, scalable, and efficient AI-powered financial systems by exposing the methodological shortcomings of some studies.

Keywords—Artificial Intelligence, Banking, Big Data Analytics, Churn Prediction, Credit Scoring, Explainable AI, Federated Learning, Financial Services, Fraud Detection, Machine Learning, Marketing

INTRODUCTION

Today, the banking sector produces a vast set of data thanks to its customers' transactions and behavior feeds. Different structured and unstructured data collected by every bank from internal and external sources hold precious information to extract and visualize data to optimize decision-making processes. According to the Digital Economy Compass 2019 of statistica, the prevision of data generated till 2030 is 612 Zetta-octets while it was 2 Zetta-octets till 2010.

The question is how to take advantage of this big data gathered and how the bank industry can maximize its profit with data analysis and artificial intelligence. How can banks get smarter?

Many national and international banks have improved their efficiency and productivity by automating their processes, developing scoring systems, and implementing customized marketing. However, they have not fully utilized the available data and AI technologies to learn from past experiences and innovate their banking practices. By incorporating data science and artificial intelligence, the banking industry can create innovative and intelligent applications that can further enhance their operations for greater efficiency and productivity.

Data-driven banking not only solves a technological but is also a strategic requirement. As consumer expectations grow, regulatory constraints get stricter, and fintech startups' competitiveness gets fiercer, traditional banks have to adapt into intelligent companies. Together AI and BDA will allow financial institutions to foresee risks, adjust services, identify fraudulent activities, and continuously monitor compliance in real time, so transforming them. Using these technologies can help new business models grow and enhance internal procedures especially in digital and mobile banking settings.

Over the past five years, increasing volumes of research have examined how AI and BDA may be integrated into fundamental banking operations including fraud detection, credit scoring, customer segmentation, churn prediction, and risk management. These studies show time and again that coupling advanced algorithms, such as ensemble models, deep learning architectures, and natural language processing, with massive datasets, often spanning tens of thousands to several million records results in

notable accuracy and operational insight [1] [2] [3] [4]. Still, many financial institutions struggle with model scalability, interpretability, and data integration even with these encouraging results.

One arranges this task as follows. The Background section outlines the basic concepts of Big Data, data analytics, and machine learning together with their evolution and applicability to modern banking. The Methodology shows the study strategy applied to evaluate and examine most recent contributions in the subject. Emphasizing credit scoring, customer segmentation, fraud detection, marketing, we underline in the Results section the main applications of artificial intelligence and BDA in banking. Especially in relation to dataset size, data quality, and algorithmic performance, the study closely examines these findings. Finally, the conclusion highlights the present research gaps and provides recommendations for next actions to further artificial intelligence-powered banking.

BACKGROUND

“Big data” first appeared in 1997 [5]. It was mentioned in a scientific article according to the Digital Library of Computing Machinery Association (ACM) as a technological challenge to visualize big data sets. In 2001, Laney [6] defines Big Data as high-volume, high-velocity, and high-variety information assets, and these are the three V’s.

Big data was named by the McKinsey Global Institute as the fourth industrial revolution in 2011 [7]. In its 2014 report, Ernest&Young defined it as the dynamic, vast, and varied volumes of data produced by people, tools, and machinery. They have added Veracity as the fourth V [8]. After that, in 2014, S. Kaiser [9] proposed to add a 5th ‘V’ which is ‘Value’, which is the contribution big data has to decision making. Since 2017, Researchers have added new V’s [10] such as Variability, Visualization, Validity, Vulnerability, and Volatility...

Data analysis is not a new concept, and it has been around for a long time. Humans have been analyzing simple data for ages. When the amount of data is small, analysis can be done quickly and easily. However, as the amount of data grows and becomes more complex, analysis becomes more challenging. The development of analytics began with the emergence of computers and has continued to advance with the progress of computer technology. In the Big Data Era, traditional methods were no longer helpful for dealing with data. Authors of [11] consider data analytics as the core of the Big Data revolution that allows us to extract value from big data. They define data analytics as the process of examining large volumes of data to learn about different individuals' spending patterns, correlations, etc., which helps industries find new opportunities to make more innovative business moves, and effective decisions.

Big Data analytics (BDA) concerns using data and tools for business decisions, it includes data analysis. This latter concerns specific actions [10]. The Data Analytics Pipeline starts with data extraction and ends with decision-making. Before addressing the analysis of data, it is necessary to fulfill the following steps: data identification, data wrangling, data storage, data mining, and data visualization.

Today, modern forms of data analytics include big data, descriptive, predictive, and prescriptive analytics. It uses artificial intelligence to further develop the outcome of the analysis. In this paper, we will focus on machine learning.

Machine learning (ML) is a fundamental component of data science. The McKinsey Global Institute in its report [7] supports that the revolution of Big Data will be driven by ML. Let us go back to the origin of ML and its evolution since it appeared.

In the 1950s, Arthur Samuel of IBM [12] introduced the term "machine learning" when he developed a computer program for checkers. He programmed it to remember the positions seen and combined this with the reward. In the early 1980s, artificial intelligence research wasn’t about algorithms but focused on logical and knowledge-based approaches. Until then, machine learning was a training program for AI. After that, it wasn’t any more training for artificial intelligence but turned to solving problems. With Big Data, machine learning has progressed to use created algorithms that can deal with large volumes of data of various forms. There are “supervised”, “unsupervised”, and “reinforcement learning”, and each one has its specific use cases and algorithms.

For supervised learning [13], we know in advance the inputs and outputs. The system develops the ability to link them. Unsupervised learning is when there is no classification of the input to train the dataset. Its objective is to describe a structure from unlabeled data. Reinforcement learning interacts with its environment to discover errors or rewards and then finds the ideal action to have the best performance. Beyond these conventional methods of learning, some advanced artificial intelligence paradigms have

been introduced into modern financial analytics to manage new types of data and decision complexity. Originally derived from traditional business intelligence, big data analytics has evolved lately into a multidimensional ecosystem propelled by advanced artificial intelligence techniques. Rising complexity and volume of banking data have brought new paradigms such Natural Language Processing (NLP) [14], Graph-Based Learning [15], and Federated Learning [16] from transaction logs and behavioral traces as well as consumer feedback. Banks can now automatically comply and personalize services more successfully by evaluating client complaints, classifying support tickets, and extracting insights from regulatory texts or contracts by means of NLP models such BERT and GPT architectures.

Another significant advance since it addresses interpretability, a fundamental difficulty in controlled environments, is explainable artificial intelligence (XAI) [17]. Especially in credit scoring or fraud detection, when machine learning models get more sophisticated, support predictions becomes ever more crucial. By use of SHAP, LIME, and counterfactual explanations, banking professionals may understand and trust model outputs; thereby, matching AI adoption with regulatory norms such the GDPR or the EU AI Act.

Moreover, federated learning offers a safe method to train models over scattered datasets, such as several financial companies, without centralizing private data. This multifarious approach protects data privacy even if group learning is still helping. Examining transactional linkages and patterns across entities helps graph neural networks (GNNs), last but not leastly popular for fraud detection and anti-money laundering (AML), to be understood. These developments greatly raise the capacity of data-driven banking outside traditional analytics pipelines.

METHODOLOGY

This paper is organized as exploratory literature research meant to assess the development and present status of Artificial Intelligence (AI) and Big Data Analytics (BDA) applications inside the commercial banking sector.

We initiated the process by formulating an extensive search query that amalgamated specific keywords including “Artificial Intelligence,” “Machine Learning,” “Classification,” “Regression,” “Clustering,” “Prediction,” “Banking,” “Finance,” “Credit Risk,” “Fraud Detection,” “Customer Analytics,” “Federated Learning,” “Explainable AI,” “Graph Neural Networks,” and “Natural Language Processing.”

Using ScienceDirect, Scopus, Web of Science, IEEE Xplore and google scholar, among other scholarly databases, the search is limited to peer-reviewed journal and conference article publications spanning 2017 to 2025. The original corpus had about 2,000 papers.

We ran a multi-tiered filtration system:

- 1) Title-centric screening to weed clearly unrelated works.
- 2) Review of abstracts and introductions with an eye toward relevance of artificial intelligence and finance industry applicability.
- 3) Thorough reading of selected works to confirm contextual richness and methodological integrity.

We used established inclusion criteria covering application in commercial banking, use of certain artificial intelligence models, availability of evaluation measures, and empirical or simulated results. Non-English publications, non-financial sector emphasis, duplicate articles, and essentially theoretical assessments devoid of practical applicability were the exclusion criteria.

We therefore conserved 153 papers, which we categorized using a theme classification system based on their main artificial intelligence uses: fraud detection, credit scoring, churn prediction, marketing analytics, compliance monitoring, operational risk, and sentiment analysis.

We conducted comparison studies spanning several angles in order to increase analytical rigor, including:

- Algorithmic diversity: Tree-based models against neural networks.
- Applied performance assessments: AUC, F1-score, accuracy, etc.
- Practical constraints: Data dimensions, latency, scalability...
- Application of advanced techniques: Explainable AI, Federated Learning, Graph Neural Networks, and Natural Language Processing.

While stressing under-researched but exciting techniques emerging in recent literature, we investigate implementation challenges in banking systems including regulatory compliance, data privacy, and model interpretability.

RESULTS

Based on the analysis of actual research, we have some important key factors on which we have to focus on improving the results, like business understanding, data preparation (problem of missing or noisy data), feature selection, proceeding time, and critical metrics depending on the situation.

There are many activities where we can use AI, such as process optimization, chatbots and voice bots, marketing, customized services, churning forecasts, security, compliance, financial assistance, and many other activities in the banking industry.

In the following, we focus on three main branches in which we can use BDA and ML in the banking sector.

A. Fraud Detection

Fraud detection is a broad concept affecting any business while having a financial or non-financial transaction. The subject is currently at the heart of studies as it needs a reliable, quick response with high precision.

The first issue is credit card fraud prevention or detection. There are also loan fraud, money laundering, and financial statement fraud.

In this context, [18] compared ten methods and evaluated precision, recall, and F1-Score, including time variance. They proved that ensemble-learning approaches (bagging, boosting, and random forest) perform better than classical methods.

Furthermore, [19] looked into machine learning techniques for detecting fraud after pre-processing. The result is that "SVM" outperforms "decision trees", "K-Nearest Neighbors", and "random forests".

Whereas the previous study compared four algorithms, another study [20] focuses on data mining and proposes a hybrid method. They combine LightGBM and XGBoost. The method outperforms both the algorithms separately and also "SVM" and "logistic regression". The advantage of this study is that it concerns a one-million-record dataset with 400 features.

From a different perspective, [21] used deep learning to detect fraudulent transactions as they are getting more difficult to see from past data. The authors used a neural network pre-processing and then compared it with Naive Bayes, logistic regression, and support vector machines to prove the excellent performance of deep learning.

In this continuity, [22] published an article for intelligent financial fraud detection in general after the pandemic (COVID-19) that accelerated economic digitalization without securing it from fraud. The papers present different types of financial fraud in various industries. The authors assume that Naive Bayes, Logistic Regression, and Support Vector Machine are interesting linear classifiers but demonstrate that graph-based detection, such as GNN, delivers exciting results.

B. Loan Default Prediction

As the core business of the banking system is to lend money and then get it back, loan default is one of the most crucial issues for commercial banks. Predicting whether a customer will repay the loan is a classification problem that aims to distinguish 'good' from 'bad payers'. Authors of [23] held a literature review of Artificial Intelligence for credit risk assessment. They concluded that, depending on the dataset size, algorithms perform differently. Support vector machine is a satisfying classification algorithm for loan default prediction as demonstrated by [24], where authors compared to Random forest, and gradient boosted that SVM outperformed. Furthermore, [25] concluded in their article that Deep Support Vector Machine (DSVM) performed better than Boosted Decision Tree (BDT), Averaged Perceptron (AP), and Bayes Point Machine (BPM). Also, [26] combined tuned Support Vector Machine, and Recursive Feature Elimination with Cross-Validation to build a performing model. On the other hand, [27] obtained the best results using Logistic Regression, Random Forest, Gradient Boosting, and CatBoost Classifier. Logistic regression also delivers better performance than other used algorithms with Stochastic Gradient Descent training, according to the study of [28].

Moreover, [29] used the CatBoost algorithm (gradient boosting on decision trees) with a document verification module, and also a customized loan module. For another case study, [30] tests different algorithms on a real world dataset with data preparation, and analysis to conclude that Random Forest and XGBoost perform well for different metrics.

The new marketing trend for any service or good is customized service. Knowing well the customer, and selling needed services are the key to attractive, and successful banks. Not only attracting new customers but also retaining the actual avoiding churning to other banks. Banks can also prepare, and design their

products based on artificial intelligence to present the appropriate product or service to the right customer at the right moment through the right channel.

Authors of [31] compared the performance of five different algorithms on a Dataset of a Portuguese bank to propose a service to suit each customer. The authors concluded that Light GBM outperforms, with reasonable accuracy, Support Vector Machine, Gaussian Naïve Bayes, Random Forest, and Extreme Gradient Boosting in a shorter processing time.

C. Marketing, Customized Service and Churn Prediction

Also, concerning marketing, [32] uses deep learning to identify the interest of a customer for a specific product. The objective is to adopt the appropriate marketing campaign to predict the attractiveness of a product. The model uses random forest deep neural networks that allow extracting information from customers' historical data.

Furthermore, for customers' retention, [33] aimed to predict clients lost with three parameters: the length of time series, the period of inactivity, and the forecast horizon. Random Forest performs well, reaching a specificity of 92%. The linear SVM also achieves good results.

Many banks are using today's Natural Language Processing for Chatbots to assist their customers, and give answers with solutions to all their requests. Also, with Fintech startups, banks can improve their customers' experience while reducing costs [34].

To improve the commercial bank's performance, data analytics, ML, and AI techniques can take place for different tasks. As a result, few applications are used like mail and document analysis, robotic process automation, and personal financial advisor or assistant. A paper discusses BDA and AI use cases in the banking industry, as well as various digital transformation applications in global and Indonesian banks [35].

Tracking spending patterns, segmenting consumers, evaluating risk, customizing product offerings, implementing retention tactics, and collecting, analyzing, and responding to client requests are all things which banks may benefit from. Predictive analytics can serve in managing teams, and individuals retaining valuable resources, and predicting needs. Predictive analytics benefit business development by improving product performance, pricing, and quality [36].

D. Explainable Artificial Intelligence

Explainable artificial intelligence is becoming vital in credit scoring, fraud detection, and regulatory compliance within the banking sector [17]. Explainable models offer then openness and interpretability, in contrast to conventional black-box models. It enables financial institutions to fulfill regulatory requirements such as the General Data Protection Regulation (GDPR) and the EU AI Act.

E. Personal Data Protection

Another distinctive application is federated learning, which enables financial organizations to collaboratively train models while protecting sensitive customer data from centralization. This strategy is particularly relevant in situations when data privacy and sovereignty are critical. Authors of [16] conducted a study demonstrating the application of federated learning in credit scoring contexts among various institutions. The findings indicate that federated learning attains accuracy comparable to centralized models while providing robust privacy assurances. This framework is particularly effective for addressing fraud and enhancing score in environments characterized by underrepresentation or scant data.

F. Compliance

Graph-based machine learning, especially Graph Neural Networks (GNNs), has recently shown considerable effectiveness in fraud detection and anti-money laundering (AML). Instead of analyzing transactions individually, GNNs model the relationships among entities (customers, accounts, merchants) to detect anomalous patterns inside a network. The authors in [15] discover complex and covert fraud tendencies using GNNs using large transaction data, hence outperforming traditional ML techniques as SVM and Random Forest. Graph-based approaches are rather successful for complex systems reliant on hidden networks and multi-layered interactions.

G. Other

Many other applications exist, such as portfolio management, asset management, and human resources management.

Also, the use of IoT (Internet Of Things) opens enormous opportunities for the banking sector to boost its sales and strengthen its customer lifetime value. In their article, [37] present intelligent support systems for the decision making process in banks.

For another purpose, and general insight, the authors of [38] studied the factors that influence the

appropriation of AI by banks proposing a theoretical model.

DISCUSSION

In addition to free datasets accessible on sites like Kaggle, the previous studies investigated in this work use real-world datasets from many countries and situations. This research produces a fundamental aspect that is the size of the dataset and its relationship with algorithmic efficiency. The investigated literature shows datasets ranging from 300 to over 1.6 million records with feature counts ranging from 3 to more than 400.

The comparison clearly shows that Support Vector Machine (SVM) shows remarkable accuracy and durability on smaller datasets (fewer than roughly 50,000 records), so displaying top performance. More sophisticated algorithms including deep learning, ensemble techniques, and hybrid models like LightGBM and XGBoost become increasingly suitable as the quantity of the dataset and the complexity of features rise. To solve dimensionality and improve runtime efficiency, these models often call for advanced preprocessing and feature selection techniques.

This link suggests that, particularly with regard to volume and feature complexity, technique choice must be closely linked with the characteristics of the dataset. Table I below lists the best-performing algorithms arranged according to dataset size, offering a good benchmark for later comparative studies.

TABLE I. PERFORMANCE OF MACHINE LEARNING ALGORITHMS BY DATASET SIZE IN BANKING APPLICATIONS

Year	Authors	Records	Features	Star Algorithm (Accuracy)
2021	Dai et al	302	3	SVM (Acc >0.85)
2020	Shivanna & Agrawal	30 000	25	DSVM (Acc = 0.822)
2019	Shoumo et al.	38 661	32	Support Vector Machine (Acc = 0.999)
2021	A. Gupta et al	41 188	17	Gradient boosting (Acc= 0.84035)
2019	SADGALI et al.	60 000	12	SVM (Acc = 0.997)
2020	Patel et al.	64 000	14	LR, RF and Catboost (Acc = 0.84)
2021	Barua et al.	181 398	41	Catboost (Acc not specified)
2018	Rajora et al.	284 807	31	Ensemble learning approach (Acc = 0.939)
2018	Pillai et al.	284 807	28	Deep learning (Acc not specified)
2020	Song Z.	1 000 000	400	Light GBM with XGBoost (Acc = 0.985)
2020	Maheswari & Narayana	1 600 000	150	Logistic regression (Acc = 0.80)

We advise that further research looks at model scaling behavior and identifies performance thresholds at which particular algorithms lose accuracy or efficiency.

Emerging artificial intelligence frameworks including Explainable AI (XAI), Graph Neural Networks (GNNs), and Federated Learning (FL) are expanding possibilities in intelligent, safe, and privacy-compliant banking even if conventional supervised learning approaches are effective for well defined problems like credit scoring and churn prediction. . The variety of artificial intelligence approaches unlocks scalable, flexible, highly customized financial services.

CONCLUSION

The present article aimed to present the actual advances concerning research in the banking sector using BDA and ML that we classified into three main branches: Fraud detection, loan default prediction and marketing. We presented some of the exciting approaches in each of these subjects, highlighting their results comparing different algorithms with mainly classification and clustering. We conclude that, depending on our purpose, there is one or some combined algorithms that deliver better results.

Machine learning, and in some cases deep learning, can have a considerable impact on the banking

industry with the large applications from the back office to front office reducing cost and time, maximizing profit and preventing losses. AI has many possibilities to offer but does not replace man. It can accompany him and advise him. It is cost and time consuming to set up. There is also an issue concerning data protection and the law concerning it. We can study these limitations to evaluate the positive results compared to the invested resources and available qualifications.

Future work should focus on benchmarking AI models in real-time banking environments, developing regulatory-compliant explainable systems, and evaluating AI cost-effectiveness in relation to implementation constraints.

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