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The Use of Artificial Intelligence in Banking Industry

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ABSTRACT
Industry 4.0, also known as the fourth industrial revolution, has altered society and the economy by introducing intelligent robotics, artificial intelligence (AI), cloud computing enormous data sets, the Internet of Things (IoT), and 3D printers, among other scientific advances. To maintain competitiveness and keep up with global competition, it is vital to adapt to modern technology. The financial sector is a vibrant market with intense competition for products and services, and advancements in information technology have led to the development of highly valuable new technologies. This essay addresses the possible advantages of artificial intelligence in the banking sector. The study utilized a Systematic Literature Review (SLR) to evaluate the current literature on AI in the banking industry. The results of the SLR demonstrate that AI has been utilized in the banking industry in a variety of ways, including credit rating models and bank collapse prediction. In establishing credit card eligibility, logistic regression models were shown to be effective, with an accuracy rate of 80.43 percent. With a precision rate of 75.7% and a recall rate of 75.7%, artificial neural networks (ANNs) were shown to be the most accurate method for predicting bank collapse based on financial characteristics. Overall, the study indicates that AI has the ability to dramatically improve the banking business by enhancing efficiency, precision, and decision-making procedures. The study has limitations and potential biases, including the exclusion of non-English language articles and the possibility of a selection bias. To explore the full potential of AI in the banking business, additional study is required.

INTRODUCTION

The fourth industrial revolution, also called Industry 4.0, is a transformation of the economy and society in combination with intelligent robotics, AI, cloud computing, the Internet of Things (IoT), and other scientific breakthroughs (Hassoun et al., 2022). To able to stay competitive and avoid going out of business because of global competition and the problem's growing complexity, there is a need to adapt to current technology (Kotabe & Helsen, 2022). In Industry 4.0, every work is involving technology, including accounting, distribution, marketing, supply chain, etc (Fig 1). It needs a lot of time and effort to work on such big data without an integrated system that helps user to process the data. Automation can be produced by IoT devices by allowing them to connect with one another, gather data, and take actions depending on that data(Munirathinam, 2020). Thus, every work involving automation system and technologies is always more effective and efficient.

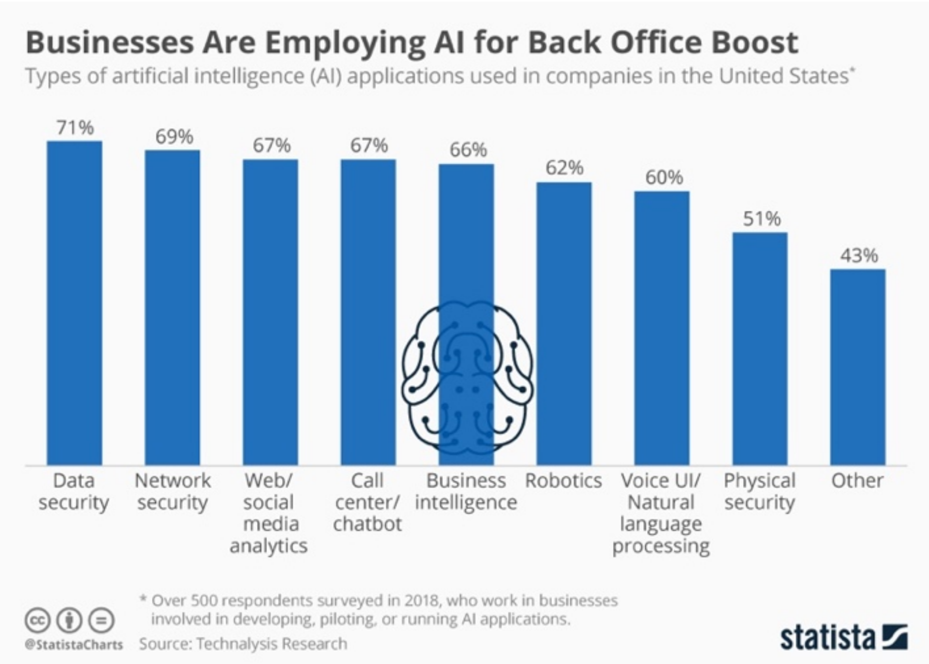

Figure 1 Business Employing AI (www.statista.com)

Intense rivalry exists for products and services in the financial sector [1]. The first ATM, SMS banking, m-banking, and internet banking all faced rivalry in the past(Dzombo, Kilika, & Maingi, 2017). With the introduction of the Internet in the late 1990s, the realization of financial transactions began(Machkour & Abriane, 2020). The development of smartphones, however, marks the true acceleration of access to the Internet(Xie, Zhang, & Zhu, 2017). The creation of new technologies that are highly regarded in the financial industry is the result of technology advancements(Bisht et al., 2022). The usage of QRIS payment, internet banking, and virtual account are a few examples on how information technology enhances transaction process in banking industry(Anderson et al., 2019).

The most important aspects of this essay are its discussion of how artificial intelligence might benefit banking industry.

METHODS

The present literature on artificial intelligence (AI) in the banking industry was examined in this study using a systematic literature review. The research process is illustrated in Fig 2. The research conducted a detailed and methodical process to discover, select, and assess relevant research from a variety of sources, including academic journals, conference proceedings, and other scholarly publications. Many electronic databases, including Web of Science, Scopus, and Google Scholar, were utilized to conduct the search.

For the research to be considered, inclusion criteria were established, such as a focus on AI in the banking industry and publication in English-language journals or conferences. Exclusion criteria, such as studies that did not fit the inclusion requirements and those that were duplicates or irrelevant to the topic, were also developed. Following the initial search, a screening procedure was done to assess the relevancy of each study based on its title, abstract, and keywords. The studies that met the inclusion requirements were then subjected to a full-text analysis, and their quality was evaluated using predetermined criteria, such as the relevance of the research issue, the validity of the methodology employed, and the credibility of the results.

Data extraction was undertaken to collect and evaluate pertinent data from the selected publications, such as the publication year, the study design, the research question, the methodologies employed, and the major findings. The review results were aggregated and presented in narrative format to give examination of the current state of AI research in the banking business. The limitations of the study were also acknowledged, including the possibility for selection bias and the exclusion of non-English language publications.

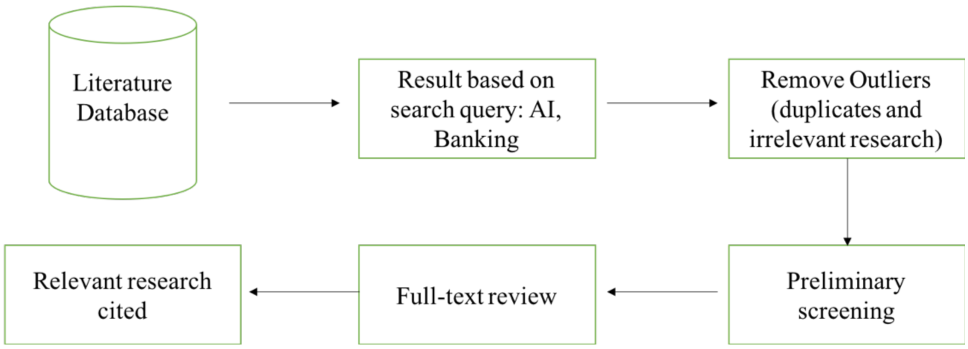

Figure 2. Research method and data extraction

RESULT AND DISCUSSION

By connecting people, machines, and technology, Industry 4.0 has changed society's socioeconomic condition in addition to its impact on many industries [7]. In order to present the information gleaned from the study of the papers, this section discusses AI-based approaches that have been used by practitioners in banking industry from various business process and researchers.

AI on Credit Rating Models

Wu et al., 2021 conducted research using dataset which was sourced from china machine learning databases. It contained financial data on a sizable bank client that had been made anonymous. Of these, 517 had credit cards and were creditworthy, whereas 183 had credit card debt. One categorical feature, education, and seven numerical attributes, including age, seniority, residency duration, income, debt to income ratio, credit card debt, and other debt, were included in this data collection. The descriptive statistics of the data presented on the Table 1.

Table 1. Descriptive Statistics of Input Variables

	Age	Education	Seniority	Duration of Residence	Income	Debt-to-Income Ratio	Credit Card Debt	Other Debt
Min.	20	1	0	0	14	0.4	0.011696	0.045584
Max.	56	5	31	34	446	41.3	20.56131	27.0336
Median	34	1	7	7	34	8.6	0.85487	1.987568
Mode	29	1	0	2	25	4.5	0.085785	7.8234
Range	36	4	31	34	432	40.9	20.54961	26.98802
Std.	7.997342	0.928206	6.658039	6.824877	36.81423	6.827234	2.117197	3.287555
Skewness	0.360703	1.198744	0.829371	0.936086	3.850475	1.093713	3.890258	2.722314

Sources: Wu et al., 2021

Table 2. Result on Traditional AI Models

Performance comparison of traditional models.

BayesNet	MP	Logistic	SVM	IBK (with 3 neighbors)	J48
75.14%	77.29%	80.43%	79.29%	77.14%	75.71%

Sources: Wu et al., 2021

The study assessed the effectiveness of numerous classic AI models, such as logistic regression, SVM, and MP, in determining credit card eligibility. The model with the highest accuracy, as shown in Table 2, was logistic regression, with an accuracy of 80.43 percent. SVM and MP followed with accuracy values that were lower.

AI on Predicting Bank Failure

Le & Viviani (2017) collected 31 ratios from the bank financial statements using a sample of 3,000 institutions, consisting of 1,438 inactive and 1,562 active banks over a 5-year period data. Table 3 provides more information regarding the extracted ratios. The researchers then utilized multiple machine learning algorithms to predict bank failure, including ANNs, k-NN, LR, SVM, and LDA.

Table 5 indicates that ANNs beat all other methods, with a precision rate of 75.7% and a recall rate of 75.3%. k-NN and LR both yielded conclusions with a precision of roughly 74%, however SVM and LDA fared badly, attaining only 71.6% and 72% precision, respectively. Notably, the TP rate was 75.3% while the FP rate was 25.9%.

Overall, the study indicates that ANNs are the most accurate method for predicting bank failure based on financial parameters, and they may have applications in the banking business.

Table 3. Measured Financial Ratio

Variables	Variables description	Expected sign
	Loan quality	
Z1	Loan Loss reserve/Gross Loans	Negative
Z2	Loan Loss provision/Net interest revenue	Negative
Z3	Impaired Loans/Gross Loans	Negative
Z4	Net charge off/Average Gross Loans	Negative
Z5	Impaired Loans/Equity	Negative
	Capital quality	
Z6	Tier 1 capital ratio	Positive
Z7	Total capital ratio	Positive
Z8	Equity/Total assets	Positive
Z9	Equity/Net Loans	Positive
Z10	Equity/Customer & short term funding	Positive
Z11	Equity/Liabilities	Positive
Z12	Capital funds/Total assets	Positive
Z13	Capital funds/Net loans	Positive
Z14	Capital funds/Deposit & Short term funding	Positive
Z15	Capital funds/Liabilities	Positive
	Operations	
Z16	Net interest margin	Positive
Z17	Net interest revenue/Average Assets	Positive
Z18	Other Operation income/Average Assets	Positive
Z19	Non-Interest expense/Average Assets	Negative
Z20	Pre-tax Operating Income/Average Assets	Positive
Z21	Non-Operating Items & taxes/Average Assets	Negative
	Profitability	
Z22	Return on Average Assets	Positive
Z23	Return on Average Equity	Positive
Z24	Inc. Net of Dist/Average Equity	Positive
Z25	Cost to Income Ratio	Negative
Z26	Recurring Earning Power	Positive
	Liquidity	
Z27	Net Loans/Total Asset	Negative
Z28	Net loans/Deposit & Short term funding	Negative
Z29	Net Loans/Total Deposit and Borrowing	Negative
Z30	Liquid Assets/Deposit & Short term Funding	Positive
Z31	Liquid Assets/Total Deposit & Borrowing	Positive

A positive sign indicates that when the ratio increases, the probability to fail decreases.

Source: Le & Viviani, 2017

Table 4. Descriptive Statistics for the 31 Financial Ratios

Ratio	Inactive banks		Active banks		F	Sig.
	Mean	SD	Mean	SD		
Z1	1.60	0.944	1.45	0.913	20.058	0.000
Z2	13.45	24.780	4.09	8.065	200.135	0.000
Z3	2.03	3.015	2.00	2.115	0.115	0.735
Z4	0.53	1.077	0.19	0.654	110.766	0.000
Z5	14.88	24.632	12.55	14.892	10.005	0.002
Z6	13.17	4.952	15.14	6.743	81.813	0.000
Z7	14.53	4.827	16.40	6.713	75.745	0.000
Z8	10.09	3.213	11.10	3.398	70.150	0.000
Z9	16.61	8.880	18.29	13.153	16.502	0.000
Z10	12.26	4.964	13.41	7.119	25.630	0.000
Z11	11.40	4.295	12.71	5.188	56.090	0.000
Z12	10.37	3.221	11.48	3.313	85.988	0.000
Z13	17.08	9.010	18.90	13.129	19.327	0.000
Z14	12.63	5.148	13.87	7.186	29.358	0.000
Z15	11.73	4.326	13.14	5.132	66.062	0.000
Z16	3.95	1.088	3.76	1.436	16.040	0.000
Z17	3.52	0.967	3.35	1.213	17.886	0.000
Z18	1.00	1.190	1.12	1.474	6.184	0.013
Z19	3.52	1.810	3.18	1.605	30.231	0.000
Z20	1.00	1.663	1.30	0.998	38.089	0.000
Z21	−0.29	0.622	−0.24	0.572	4.716	0.030
Z22	0.67	1.238	0.98	0.780	67.328	0.000
Z23	7.28	11.764	8.83	6.525	20.391	0.000
Z24	1.88	11.626	5.27	5.961	103.154	0.000
Z25	69.85	32.613	67.83	14.711	4.909	0.027
Z26	1.46	1.416	1.48	1.260	0.081	0.777
Z27	65.16	13.438	65.97	13.338	2.763	0.097
Z28	78.41	20.623	78.06	17.342	0.263	0.608
Z29	73.60	15.244	75.59	15.583	12.394	0.000
Z30	9.72	10.426	7.71	8.077	35.414	0.000
Z31	9.24	9.080	7.50	7.843	31.809	0.000

Source: Le & Viviani, 2017

Table 5 showed that, No matter how you measure performance (75.7% accuracy and 75.3% recall), ANNs outperformed all other approaches. As can be observed, k-NN and LR both produced findings with approximately 74% precision. SVM and LDA perform badly, with just 71.6% and 72% accuracy, respectively.

Table 5. Experiment Result

Method	Confusion matrix		Precision	Recall	ROC Area	PRC Area
ANNs_2	2415	444	75.7%	75.3%	81.9%	80.3%
	892	1649				
8_NN	2455	404	74.1%	73.1%	81.1%	78.3%
	1048	1493				
LDA	2185	674	72.0%	72.0%	77.6%	75.8%
	836	1705				
LR	2235	624	73.9%	73.9%	79.6%	77.3%
	785	1756				
SVM	2121	738	71.6%	71.6%	71.5%	65.5%
	794	1747				

Table gives the accuracy measures for the five bank failure prediction techniques: ANN with two hidden layers (ANNs_2), k-NN with 8 neighbors (8_NN), Linear discriminant analysis (LDA), Logistic Regression (LR), Support Vector Machine, (SVM). **Precision** is the fraction of those predicted positive that are actually positive. **Recall** is the fraction of those that are actually positive which were predicted positive. **ROC area**: Receiver Operation Characteristic curve. **PRC Area**: Precision/Recall plots.

Source: Le & Viviani, 2017

On Cyber Threat Detection

Noor et al study.'s from 2019 looked at the effectiveness of several machine learning models for identifying cyberthreat actors (CTAs). The 36 threat actors that have been identified during 2012–2018 are described in 327 thread reports from 26 sources, according to the researcher (see Table 6). The experiment result shown in Table 7 which shows the total values that was calculated by averaging on each CTA types. Later researcher found that DLNN is the best tools to accurately predict threat detection (94% accuracy and 90% precision). k-NN was the most inaccurate tools for the threat detection.

The research found that the naive bayes, RF, and DLNN models could successfully detect CTAs with good accuracy, precision, recall, and f-measure. Feature selection enhanced the Naive Bayes model's precision, recall, and f-measure but did not appear to enhance the models' attribution accuracy. Nonetheless, the accuracy, recall, and f-measure decreased with RF and DLNN models.

The study reported low accuracy, precision, recall, f-measure, and false-positive rate when evaluating the models using the ATT&CK dataset (the Adversarial Tactics, Techniques, and Common Knowledge). This may be related to the restricted quantity of data accessible in the dataset, as there was only one occurrence of a high-level indicators dataset for each CTA. The study was therefore unable to analyze the attribution of cyber assaults using cross-validation methodologies. Overall, the study emphasizes the significance of analyzing machine learning models using many datasets to determine their efficacy in identifying and attributing cyber intrusions. It also indicates that feature selection may not necessarily increase the accuracy of machine learning models' attribution.

Table 6. Summary of CTA

Cyber threat actor	Country	Motive
APT1	China	Espionage
admin338	China	Espionage, stealing trade secrets
APT 12	China	Espionage
APT 16	China	Espionage and spear phishing
APT 18	China	Espionage
APT 28	Russia	Espionage, data theft and reputation damage
APT 29	Russia	Espionage
APT 3	China	Stealing Intelligence Information
APT 30	China	Data theft for political gain
APT 32	Vietnam	Mass digital surveillance
APT 34	Iran	Espionage
Equation	USA	Espionage, data theft, system control
Fin 5	Russia	Financial gain, stealing personally identifiable information (PII) and payment card data
Fin 6	unknown	Stealing payment card data
Fin 7	Russia	Financial gain
Gamaredon	Russia	Espionage
GCMAN	Russia	Transferring money to e-currency services
Group 5	Iran	Penetrating systems and networks
Ke3chang	China	Espionage
Lazarus	North Korea	Espionage, financial loss and reputation damage
Lotus Blossom	China	Espionage
Magic Hound	Iran	Espionage
Menupass	China	Espionage and data theft
Moafee	China	Stealing trade secrets
Molerats	Middle East/Gaza	Espionage
Axiom	China	Espionage
Bronze Butler	China	Espionage
Carbanak	unknown	Financial gain
Cleaver	Iran	Data theft and service access
Copy Kittens	Iran	Espionage
Darkhotel	North Korea	Compromising personal gadgets of high-profile individuals
Deep Panda	China	Data theft
Dragonfly	Russia	Espionage
DragonOK	China	Espionage and spear phishing
DustStorm	China	Espionage and severe damage
Fin 10	unknown	Financial gain and victim extortion by stealing PII, file records and correspondences

Source: Noor et al., 2019

Table 7. Experiment Result

		Accuracy	Precision	Recall	F-measure	False positive rate
Naïve Bayes	Attribution (without IG)	88%	89%	82%	0.83	3%
	Attribution (with IG)	86%	90%	84%	0.84	3%
	ATT&CK	52%	66%	59%	0.53	9%
KNN	Attribution (without IG)	68%	69%	70%	0.67	7%
	Attribution (with IG)	68%	71%	71%	0.68	7%
	ATT&CK	52%	66%	59%	0.53	9%
Decision tree	Attribution (without IG)	82%	76%	74%	0.73	4%
	Attribution (with IG)	72%	76%	74%	0.73	2%
	ATT&CK	3%	0.10%	2.78%	0.002	3%
Random forest	Attribution (without IG)	88%	92%	89%	0.89	3%
	Attribution (with IG)	83%	88%	82%	0.84	2%
	ATT&CK	17%	16%	22%	0.14	15%
DLNN	Attribution (without IG)	94%	90%	89%	0.89	3%
	Attribution (with IG)	86%	91%	88%	0.88	2%
	ATT&CK	11%	17%	18%	0.13	15%

Sources: Noor et al., 2019

CONCLUSION

Industry 4.0 has had a substantial impact on the socioeconomic state of society and has revolutionized a variety of industries [10]. The financial industry is not an exception; practitioners and researchers have utilized AI-based technologies to enhance numerous business operations. The artificial intelligence movement has greatly improved e-finance, as previously manual or statistical model-based tasks have evolved into more intelligent, autonomous, and predictive ones

The research covered in this paper shows the efficacy of several machine learning algorithms in the banking sector based on previous research. Wu et al. (2021) reported that logistic regression was the most efficient approach for assessing credit card eligibility, whereas Le & Viviani (2017) found that artificial neural networks (ANNs) were the best accurate method for forecasting bank failure based on financial characteristics. Noor et al. (2019) discovered that naïve bayes, RF, and DLNN models is a moderated tools to detect cyber threat actors.

It is vital to remember, however, that accuracy is only one of several metrics used to measure the effectiveness of a machine learning model, and it may not always provide a comprehensive view of the model's usefulness. Depending on the application, other metrics such as precision, recall, and F1 score may also be significant. Moreover, the generalizability of the conclusions may be constrained by the specific dataset used in the study. Overall, these studies illustrate the potential for AI-based approaches to improve decision-making and increase efficiency in the banking business. AI will undoubtedly play a larger role in the banking industry as technology continues to evolve, allowing financial organizations to better manage risk, improve customer experience, and increase profitability.

This study has identified a number of frameworks that have been put out by business professionals for AI integration. As a result, a uniform framework is needed that industrial practitioners from various fields may utilize to incorporate AI into their industrial processes. Despite the study's concentration on AI/ML, there is still a lot of ground to cover in the vast topic of Industry 4.0, which cuts across many other industries. The primary objective of this study, which was exploratory in nature, was to give a comprehensive review of the technologies and research fields related to banking-related artificial intelligence in the context of Industry 4.0 to non-specialists.

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