IARJSET
ISSN (O) 2393-8021, ISSN (P) 2394-1588
International Advanced Research Journal in Science, Engineering and Technology
Impact Factor 8.066 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 10, Issue 12, December 2023
DOI: 10.17148/IARJSET.2023.101225

ENHANCE THE BANKING SECTOR COMPLIANCE PROCESS THROUGH ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING TECHNIQUES

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Abstract: Artificial intelligence (AI) is gaining popularity in a variety of fields, including business and society. However, while investment banking and backend services were among the first banking applications to successfully integrate artificial intelligence, AI is now mostly applied in areas where there is no direct client contact. Because of the importance placed on customer relationships in commercial banking, the deployment of artificial intelligence has received little attention. Artificial intelligence in commercial banking has the potential to have a substantial impact on corporate procedures and client relationships, which could open up new research areas in the field of behavioral finance. According to our research, artificial intelligence can assist commercial banks in reducing lending losses, increasing payment security, automating compliance-related labor, and improving consumer targeting. Researchers are worried about several concerns, including realizing technological advantages, implementing artificial intelligence into commercial operations, and ensuring that users are comfortable with the technology. As a last recommendation, we encourage you to sketch out an overall research strategy for behavioral finance science in the future.

Keywords: Banking Sector, Compliance Process, Machine Learning, Artificial Intelligence

I. INTRODUCTION

In the last decade, there has been a growth in the number of digital start-ups operating in the financial services market [1]. This financial technology (Financial companies) corporation claims that they have massive amounts of data and powerful computational platforms capable of understanding it [2] [3] have resurrected debates on design [4] and the purpose of the financial sector [5] [6].

Financial services and product organizations have long relied on probability and statistical models to create forecasts about their future performance levels. As a result, financial technology (Financial companies) is not a brand-new notion [7]. Changes in the quantity of something can occasionally have an impact on the quality of that thing. As a result of the incorporation of increasingly complete datasets and fresh methods of analysis, financial companies are expected to use increasingly intricate algorithms to anticipate the payback likelihood and profitability of consumers. [8]: Future-oriented thinkers predict that artificial intelligence will eventually replace human decisions about a borrower's creditworthiness with increasingly sophisticated, objective, and analytical models that are based on data mining and machine learning [9]. If such breakthroughs do occur, however, they may be in breach of other legal requirements [10].

II. EVOLUTION OF AI

Allan Touring asserted in the early 1950s that humans use knowledge that is readily available to them and reasoning to make good decisions and overcome barriers; thus, why can't robots do the same thing? Computers and information systems were still in their infancy until the late 1970s. When David Rumelhart and John Hopfield proposed the concepts of deep learning in the 1980s, they were considered revolutionary because they allowed computers to learn from their own and other experiences [11]. For much of the twentieth century, the emphasis was on expanding computing power and integrating it with logic programming to lay the groundwork for commercial artificial intelligence. Despite this, advancements in artificial intelligence (AI) have been disappointingly modest in recent years. Deep Blue, an IBM computer that was able to compete with humans at chess in the late 1990s, ignited a wave of interest in AI that has continued for the past two decades [12]. It had been decades since a computer had defeated human intelligence, but Deep Blue had done so against the world's finest player, Gary Kasparov.

An illustration of how artificial intelligence is predicted to develop in the coming years may be found in the following section:

Lending Models Based on Artificial Intelligence Because of the nature of the risk involved in credit and lending decisions, Shorouq et al. [13] proposed a model on AI model for lending decisions. When this notion is implemented, financial institutions such as banks and credit unions will be able to exert complete control over the loan process from the outset to its conclusion. As a result of artificial intelligence models such as these, only applications with low credit risk will be approved, while applications with high credit risk will be rejected. To establish a person's creditworthiness, banks rely on traditional statistical procedures, which are normally carried out manually. Traditional credit rating procedures are used to build credit scores that are used to make lending choices for both corporations and individual consumers. Typically, payment history and transaction data obtained from banks and other financial organizations serve as the starting point for credit rating algorithms.

The conventional methods of computing a credit score from modest collections of structured data, such as statistical analysis, decision trees, and regression, are the most commonly used approaches for this purpose [15]. With the advancement of technology comes access to a wide range of additional data sets that may include semi-structured or unstructured data from social networking activities, online search, consumption of content from online and other shipping activities, as well as text message activity. Lending institutions can use this data to make more informed lending decisions. According to Stephan et al. [14], using machine learning tools and algorithms, credit evaluation may be broadened to include qualitative traits such as spending patterns, ability and willingness to pay, and other factors that are not currently considered. When incremental data sets are used in conjunction with credit applications, it is possible to successfully and effectively segment the credit applications using the quality of a borrower. As a result, data privacy and protection rules may also apply to this method and lending institutions must be on the lookout for policy issues to avoid policy challenges.

III. ARTIFICIAL INTELLIGENCE (AI) IN THE FINANCE SECTOR

The use of mobile devices is becoming increasingly popular among clients, and new credit intermediaries are taking advantage of this growing popularity. The purpose of these platforms is to reduce a significant portion of the costs involved with credit scoring, lending, and servicing the vast consumer debt sector [16]. As a result of eliminating the need to gather time-consuming paper applications and their related documents, digital credit determinations help to reduce underwriting expenses.

Furthermore, improved statistical models and predictive analytics have been shown to boost lenders' ability to forecast default and prepayment risks in addition to these benefits [17]. Financial companies components enable automated decision-making (ADM) that claims that these platforms ensure a reduction in the discrimination risk over protected legal groups since the computer engine cannot perform the mental processes associated with human discriminatory action[18]. Depending on the components, ADM is capable of eradicating animosity among people [19]. AI technology can be used to analyze data acquired and processed through photos or speech data to uncover unconscious bias and prejudice. 46. Concerns concerning disproportionate impacts are also key considerations.

To increase their predictive abilities, artificial intelligence relies on supervised or unsupervised models to enhance its output as a result of the examination of enormous amounts of data. In contrast to unsupervised learning, which is based on a lack of training data, supervised learning makes use of data that has been labeled and categorized by a trained expert [20]. Unsupervised learning, which can be resource-intensive because it infers information from the data set, compares the data set against a large number of potential patterns in the data set. 49.

Neural networks, which are common algorithms in supervised learning, are designed to replicate the human brain to provide the results [21]. In a similar way to how classical algorithms do, AI can provide an analytical predicate for ADM in a similar way [22]. Instead of attempting to comprehend modern artificial intelligence reasoning, it would be more productive to attempt to map out all of the synapses and chemical reactions that take place in a manager when deciding whether or not to grant a request [23].

IV. MACHINE LEARNING IN COMPLIANCE BANKING

It is possible to automatically detect patterns in data by employing machine learning techniques [24]. The machine learning uses patterns it identifies to generate predictions about the future based on the data it receives as input [25]. Methods such as this rely on logic and complex decision-making to get to the heart of difficulties like this one, and they are not without their limitations [26].

DOI: 10.17148/IARJSET.2023.101225

Through the use of machine learning, an algorithm or an ensemble of algorithms that has access to a significant amount of data can achieve constant improvement in a given job [27]. It is critical to understand that the term learning is being used metaphorically rather than in the sense of the broader idea alluded to when people speak about human learning [28]. A computer is not required to engage in cognitive skills such as thinking or grasping abstract conceptions for machine learning to be effective. Therefore, artificial intelligence systems are susceptible to pursuing types of investigations that an experienced financial professional would dismiss as suspect [30].

Instead, machine learning makes use of inductive techniques to learn appropriate rules for a certain task from a large amount of data, which is then used to do the task [31]. An intelligent algorithm strives for high levels of accuracy in the performance of a certain task, even when it does not think in the same way that humans do. An idiot savant can be related to machine learning in that it can reach conclusions faster than a person can, similar to how a calculator can multiply 15-digit digits faster than anyone else in the world. Adding extra dimensions of desired outcomes to the solution space may result in improved machine learning in the long term, according to research [32]. Although it is possible, it is challenging to approach a machine learning system with a complicated and confusing task.

Learning algorithms are not able to be replicated with complex cognitive and emotional processes that distinguish human thought processes from those of other animals. Instead of depending on intuition, these algorithms make predictions based on historical facts [33]. It will be a long time before computers can even begin to simulate the decision-making process of the human brain in a computer simulation, let alone complete it.

Several aspects of machine learning must be considered to discern between human and computer decision-making. In total, three groups of data are used in the initial analysis: training data, verification data, and testing data. Machine learning can learn from the data by utilizing these three subsets of information. By studying the training set, it is possible to learn an initial group categorization rule [34].

These rules are validated on the validation set to fine-tune the parameters of their classification rules [35]. The final step involves applying the optimized rules to a test set, and the results of this stage are used to determine the level of confidence and support for each rule. The confidence level of a rule relates to the frequency with which the test set objects adhere to the rule in question. This statistic is used to assess the accuracy of algorithm predictions. 70

When developing algorithms for these circumstances, it is critical to evaluate each algorithm output in terms of the desired result. This allows the ML to learn the data at its disposal, which aids in the machine's ability to learn [36].

When training algorithms, it is usual practise to follow a four-step procedure [37]. A good example of this approach is the Google Image picture recognition learning system, which is used for image recognition training. The algorithm is supplied with a set of photographs that are already well-known to it at the outset. To make matters even more challenging, the algorithm combines nonlinear processes into its basic rules, thus complicating the situation.

To recognize chunks, some concepts may or may not be related to our traditional procedures [38]. As an alternative, they could make use of viewpoints that are not now available to us [39]. In the third step, a test set is created to put the algorithm rules to the test [40]. The algorithm makes adjustments to its internal rules in response to the outcomes of the test [41]. Until the algorithm is capable of categorizing photos reliably and consistently, these processes will be repeated endlessly [42].

Machine learning is feasible for algorithms to improve over time in their ability to do a task successfully. Especially in situations where desirable outcomes can be assessed or otherwise evaluated and scored, machine learning technologies are becoming increasingly popular throughout society. These kinds of approaches are frequently used in classification jobs, for everything from identifying spam emails to making medical diagnoses [43]. They must, however, consider far more ethical considerations when shifting from analyzing cancer to evaluating people.

AI-powered Assistance in customer experience

The concept of using AI in financial markets was initially introduced by Nicholas et al. [15] in 2001, and it has since gained widespread acceptance. As a result of this development and adoption, chatbots have now been developed and widely adopted by large commercial banks all over the world. In modern-day versions of chatbots, automated systems based on Native Language Processing (NLP) may interact via voice and text. These systems, which are powered by machine learning and enable the ability to self-improve, provide clients with on-demand assistance and transaction support, among other things. The introduction of chatbots in the financial services industry will have a significant positive impact.

DOI: 10.17148/IARJSET.2023.101225

AI Applications for Insurance

In emerging markets, the insurance industry is gaining in popularity as the economy grows. When it comes to functions such as claim processing, underwriting, risk assessment, and actuarial, artificial intelligence adoption may be observed [44]. Due to this, top insurance providers use DL for pricing and marketing of highly personalized insurance plans, gathering real-time, detailed data from sensors, linked devices, and location monitoring and digital footprints, among other sources [45]. Machine learning is the key building block of these systems, which continually learn from claims history data sets and create estimates for claims. Machine learning is a fundamental building block of these systems. As a result of this technology, insurance claim processing time and expenses can be significantly lowered [46].

AI in for Fraud Detection

Financial fraud is defined by Dahee et al. [17] as the unlawful use of mobile transactions and platforms as a result of identity theft, which ultimately leads to fraudulent activities. Financial fraud in the broadest sense includes the illegal use of cash or credit cards, unauthorized transactions, fraudulent claims, and fund transfers carried out under the guise of a stolen identity, among other things. As AI has improved over time, machine learning has progressed to the point where it can detect fraudulent transactions. The algorithm constructs predictive models based on previous data analysis performed [47]. The use of transaction data that has been flagged as suspicious by the investigator and typical fraud detection systems can be used to supplement previous data if it is insufficient for investigation purposes [48]. When combined data is utilized in a neural network, the algorithms can be used to construct prediction models capable of creating patterns and sets with the fine detail that is only possible with combined data as input [49]. Fraud investigators in the financial industry would substantially profit from these arrangements, which provide a dependable mechanism of an accurate forecast and estimate tool, which would greatly assist them in their investigations [50].

AI in financial policy

To close any potential holes that may exist in the future and avoid another financial crisis, banks have boosted the number of compliance officers on their payrolls. Manually monitoring the compliance procedures of a large financial institution, on the other hand, proved to be unfeasible due to the enormous volume of transactions that take place throughout the world [51]. As Liebergen [18] argues, new regulations established following the financial crisis compelled institutions to report comprehensive data, which typically included information about their business models and balance sheets. Multiple other regulatory requirements, including new solvency regulations known as the Comprehensive Capital Analysis and Review (CCAR), increased reporting requirements to such an extent that they were compounded by a factor of several hundred or thousands [52].

Artificial intelligence technologies are now being used in financial organizations to handle anti-money laundering programmes, know-your-customer standards, etc. In addition, financial institutions use artificial intelligence techniques to assist their governments in tracking terrorism financing and money laundering, as well as other global problematic transactions, such as international trade fraud. Many big banks are already using artificial intelligence systems, and more are expected to do so in the next two or three years [53].

V. DISCUSSION

The dimensions of Table 1 will be included in the review. To establish a foundation, this article will cover the numerous aspects of commercial banking from the perspectives of technology, data sources and data types, performance, and management, as well as the anticipated business impact and managerial implications. Second, we will outline and summarise the issues raised in the academic literature about AI in commercial banks:

Table 1: Business Areas in Commercial Banks

Authors	Business Area	IT systems used
Casu, et al.[64]	Lending	SAP
Casu et al. [64]	Managing deposits	ATM network to cash depositing [63] Server-based IS [66] SAP modules [67] ATM networks [68]
Krueger and Leibold [66]	Payment Processing payments	Server-based IS and Digital payment [70]
Butler and O'Brien [71]	Compliance with regulations	Compliance with manual labor and Research systems
Krishnan et al. [65]	Marketing and sales	CRM [69] and Salesforce automation

DOI: 10.17148/IARJSET.2023.101225

Lending using AI

From both a technological and a business aspect, artificial intelligence has a huge impact on lending. From a technological aspect, AI enables commercial banks to (1) make more accurate forecasts using data types that were previously underutilized and (2) deploy innovative algorithms in the analysis of customer data [54] [55]. It is also important to note that the use of AI in lending is considered to have certain implications for the banking business. Commercial banks, whether they are examining credit cards, corporate loans, or consumer loans, can save money by making more precise evaluations of credit risk than they currently do [56]-[58].

Business Impact

It is also necessary to look into how the use of artificial intelligence affects business operations. Khandani et al. [59] forecast that the cost savings will range from 6% to 25%, but they do not go into detail regarding how these savings will express themselves, where they will manifest themselves, or when they will manifest themselves. The cost reductions of banks utilizing various artificial intelligence algorithms for different forecasting intervals were simulated by Butaru et al. [60], who reported possible cost savings ranging from 9% to 76% for various forecasting intervals. According to studies, banks might save a significant amount of money by incorporating artificial intelligence into credit risk management. The research demonstrates that translating predictive models into business metrics is not a simple procedure to do.

Processing payments

Concerns about controlling the growth of the payment network and identifying and avoiding fraud are two of the most critical issues raised in the articles we reviewed. Through the identification of patterns in large datasets of transactions, artificial intelligence assists in the identification of potentially fraudulent transactions. Beyond anticipating ATM network utilization and improving business operations, artificial intelligence may also help bank branch infrastructure managers increase the efficiency with which they operate their branch networks. According to research, AI has the potential to improve the overall security and efficiency of even the most complicated networks.

Scaling or Managing the Business Infrastructure

It is uncommon to find research on the application of artificial intelligence in the administration of payment infrastructure. Using neural networks, which they developed themselves, Serengil et al. [61] forecast the cash flows at ATMs. When Grozin et al. [62] attempted to forecast the quantity of money required in Russia to fill cash dispensers, they employed SVMs and random forests to make their predictions.

Lázaro et al. [63] go a step further, proposing (1) a strategy for increasing the number of cash deliveries to each branch under review, and (2) addressing how to incorporate projections into business processes to maximize cash delivery. Some criteria including payroll of employees and the amount of loans disbursed, are used to classify branches into more manageable categories.

After they have completed this, they will create profiles of the various segments of a Canadian bank. To be more specific, the branches are profiled based on their overall efficiency as well as the amount of production produced by each person in the branch. Bank managers will be able to get a better sense of how their branch is doing because they will use their procedures. They will also be able to find operational inefficiencies.

VI. CHALLENGES AND FUTURE CONSIDERATIONS

It has opened up new avenues for risk management, data management, and credit analysis with vast amounts of data collected, thanks to the decreasing costs of storage and server, computation, bandwidth, and processing, and the resulting reduction in processing costs. With the use of the IoT, AI, and ML, financial institutions will be able to replicate human decision-making. Paul et al. [20] stated that the banks are neither prepared nor able to deal with this type of transformation in the short term or long term.

So far, financial technology (Financial companies), which offers organizations the necessary technology would act as a partner in the efforts of banks and financial institutions to incorporate AI. It is expected that the financial technology industry will be equipped for the next level of IoT and quantum computing, which will experience exponential growth in the next few decades.

VII. CONCLUSIONS

AI can be deployed across the board in the basic operations of a commercial bank. For lending, AI can be utilized to generate exact estimates based on data types that were previously unavailable. By studying these underutilized data types,

IARJSET

ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.066 ⸎ Peer-reviewed & Refereed journal ⸎ Vol. 10, Issue 12, December 2023

DOI: 10.17148/IARJSET.2023.101225

credit risk models may be improved, revenue can hence be increased. It is possible to increase the security of payment processing for clients by using AI for the detection of money laundering and fraud. As rules build up, artificial intelligence can assist banks in processing them more quickly, identifying suspicious behavior within their ranks, and notifying the appropriate authorities when a customer participates in problematic behavior. AI can be used in marketing and sales to give clients things that are appropriate for their needs and to increase the accuracy with which customers are targeted. Commercial banks can use AI to help with deposit and account management, such as lowering the cost of cash deposits and providing new services to customers, which is a good idea.

Risk management utilizing artificial intelligence can result in improved profit margins if the artificial intelligence model is recorded in combination with legal standards. Using artificial intelligence, it is only possible to increase the efficiency of marketing and compliance management while also addressing the issue of privacy. If AI is integrated into the processes of banks, the bank infrastructure can be handled more cost-effectively.

The findings of the review, in light of the behavioral finance literature, opened the door to several new research possibilities. Several papers have examined the potential application of artificial intelligence to the study of investor psychological and behavioral traits. According to the authors, a greater amount of research is needed to determine the elements that make AI-based financial services interesting and desirable to customers. Further investigation into how people and artificial intelligence interact in the course of their daily work and in the course of making decisions has the potential to be fruitful. In addition, the authors recommend intriguing directions for further research into how corporate decision-makers think and act in their respective organizations. Finally, it looks like more research is needed to figure out how to properly record AI-based services so that they can be reported to the authorities.

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DOI: 10.17148/IARJSET.2023.101225

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DOI: 10.17148/IARJSET.2023.101225

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