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A STUDY REGARDING THE USE CASES, CHALLENGES AND FUTURE PROSPECTS OF ARTIFICIAL INTELLIGENCE IN FINANCE

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ABSTRACT

As technology has become an imperative part of fields across the world, financial methods too are now evolving to adapt themselves to the technological framework, with implications in Artificial Intelligence (AI). AI provides greater eflciency, makes complex tasks simpler, processes mass data and provides accurate results. The main objective of this study is to identify the benefits of AI in finance based upon the review of current literature. The paper is divided into three main categories: The first part summarizes the use cases of Artificial Intelligence in Finance which helps us draw inspiration and make accurate predictions for the future prospects of AI in Finance, the second part of the paper discusses the challenges that Artificial Intelligence poses in finance to understand the shortcomings that we have to keep in mind while expecting the future prospects of AI in Finance and the third part of the study highlights the future prospects of Artificial Intelligence. The paper aims to serve as a comprehensive review of Artificial Intelligence in Finance.

Key Words: Artificial Intelligence, Finance, Challenges, Artificial Intelligence in Finance, Use Cases of AI in Finance

1. Introduction

Artificial Intelligence (AI) is a branch of science that deals with helping machines find solutions to complex problems in a more human-like fashion (Nandadeepa, 2014). In the last few years, there has been an upsurge of AI in finance, with its applications in banks, fintech, regulators, and insurance firms. AI uses a knowledge database of facts to characterize the system's domain of proficiency and processes mass data to form predictions and consequently helps a company draft their plan of action leading to an increase in profits and consequently economic growth

(Appelbaum et al, 2017).

This implementation of Artificial Intelligence in finance will produce competitive advantages for Finance and Accounting firms, by improving their efficiency, reducing their costs, and enhancing their productivity and quality of goods and services offered to consumers. These competitive advantages also bear benefits for the consumer by providing products of increased quality and personalized services.

With these benefits, however, come certain risks that Artificial Intelligence may create in Finance. These vary from intensified financial risks to risk of bias, unfair or discriminatory consumer results, or data mismanagement and misusage. Moreover, the lack of general understanding of Artificial Intelligence model processes could give rise to potential pro-cyclicality. While many of the potential risks associated with AI in finance are not unique to this innovation, the use of such techniquescould further intensify these vulnerabilities due to the complexity of the techniques used, the dynamic adaptability of these techniques and the level of autonomy associated with them (Wall, 2018).

Focusing on the above discussion, this paper is divided into three main parts. The first part of the paper talks about the implications of Artificial Intelligence in finance which includes an analysis of Artificial Intelligence in financial monitoring and secure financial transactions with central focus on Intrusion Detection and Phishing Detection, Stock Market Prediction using IDS, and Robotic Process automation when special emphasis on Banks and Insurance. The second part of the paper talks about the challenges that Artificial Intelligence in Finance face. These challenges are primarily concerned with the availability, locality and volume of data and the continuous inflow of new data that hampers the accuracy of the results produced. The last part of the paper talks about the future prospects and opportunities for AI to grow in finance based on artificially intelligent financial transactions in E-commerce, Global and cross market prospects of artificially intelligent finance and implications in intelligent currency such as blockchain.

Paper is based on secondary data collected from various online sources such as IEEE, Google Scholar Articles and the International Journal of Technology and Finance, Data were suitably analyzed to get answer to the objectives framed for the study.

2. Objective

2.1 To shortlist the already established Use Cases of Artificial Intelligence in Finance. This will help us draw inspiration and make accurate predictions for the future prospects of Machine Learning and Artificial Intelligence in Finance.

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2.2 To research the challenges faced during the incorporation of machine learning in Finance. This will help us understand the bugs and shortcomings that we have to keep in mind while expecting the future prospects of AI in Finance.

2.3 To research the future prospects and opportunities for AI and ML to grow in finance.

3. Artificial Intelligence in Finance

3.1 Financial Monitoring and Security in Business Transactions:

In the 21st century, technology is employed in every imaginable field at an unprecedented rate. As technology enters the field of finance, there becomes a demanding need to address the security and privacy of allied cyber threats which are constantly increasing. In recent years, Artificial Intelligence has become an integral part of the security and privacy of various applications. According to the ESMA. 2016 Annual Report (IEEE), out of seven billion people in the world, about six billion rely on mobile phones or other smart gadgets for banking, shopping, financing, internet-of-things (IoT), and blockchain applications. There is a high chance of data leakage and theft. Malware too is triggered by corrupt system routines, unauthorized network access to resources. Several aspects of Artificial Intelligence help overcome these issues. Some machine learning applications in security are as mentioned below:

3.1.1 Intrusion Detection and Prevention:

In previous years, technology has advanced vastly in the Finance and Business sectors. Both parties, that is the customers, and the businesses use Internet applications to handle their finances and therefore, securing this financial data is now the primary concern (Shon et al 2017). The intrusion detection system (IDS) provides a defense against the risks associated with internet finance. IDS uses approaches such as packet payload analysis (Vidal et al 2017), pattern propagation and bro language.In addition to these, schemes for ad-hoc networks are also developed to detect attack patterns and to provide a defense mechanism in the network (Sagar, 2020)

3.1.2 Phishing Detection

Phishing is an unethical practice that is used to manipulate the personal and sensitive information of the victim by tricking him or her into visiting fake web pages to mimic the original website . Phishing attacks manipulate a victim's personal and sensitive information by hacking their email and social network accounts. To identify phishing attacks, many AI based approaches have been proposed such as DNS-based blacklist, automated individual whitelist, heuristic, and visual similarity. These Artificial Intelligence based techniques can automatically detect zero-hour attacks effectively on a large scale basis (Khonji et al 2020).

3.2 Making Investment Predictions

Stock Market Prediction aims to attain the estimated future value of the financial stocks of a company. The use of Artificial Intelligence has made these predictions more accurate based on the values of current stock market indices by training on their previous values and processing this mass data. Artificial Intelligence employs different models to make predictions accurate.(Parmar et al., 2019). Predictable activities include the exit event of a company, funding events in a given period of time , key financial goals that a company will achieve, predicting investment relationship between companies and investors, generating investment recommendations for investors, predicting a company valuation and classifying companies by industry (Ferrari and Muffatto ,2021).

3.3 Process Automation

Traditionally, companies across various industries employed an array of IT tools and processes (workflows) that were an amalgamation of automated and manual steps. The manual steps performed across these industries required a lot of constant physical and mental manpower, were subject to human errors, decreased employee motivation due to monotonous, repetitive tasks, degraded productivity, and increased operational costs. The automated steps too, had their own downsides as a result of the implementation of multiple IT automation solutions which added up license/development/maintenance cost, increased integration time stamps, continuous patching of code to fit underlying business logic changes (Martins et al, 2020)

Robotic Process Automation (RPA) has recently emerged as a game-changing technology outperforming the various solutions that have evolved from the Business Process Management (BPM) industry over the years. Robotic Process Automation (RPA) works with Artificial Intelligence to detect objects on the screen and take related action (Martins et al, 2020). When a programmer wants to automate a series of tasks for a given objective as a work-flow, dedicated scripts are used. With RPA, the automation process enables the programmer actions by recording the manual execution using the Graphical User Interface (GUI). The RPA stores each menu click and key, then the process is repeated as many times as necessary.

3.3.1 RPA in Financial Banking

The Banking industry deals with gigantic amounts of financial data on a daily basis and so it is

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essential for banks across the world to deal with this sensitive dataset with high precision and security. RPA minimizes the manual processing of data required and eliminates the errors generated by automating various processes using AI. These include:

- Accounts Payables & Receivables – RPA automates the vendor invoice processes and payment made to the vendor account post reconciliation. RPA also processes incoming payments and manages the clearance of customer dues. (Devarajan, 2018)

- General Ledger – RPA automates the procurement of financial data, assets, liabilities, revenue, expenses and updates GL with right information (Devarajan, 2018).

- Credit Underwriting – RPA can automate the verification of income/expense/exposure of credit applicants within the internal and external databases.

- Credit card processing – RPA can automate various time-consuming processes like document collection, credit checks, background check and determine if the customer is eligible for credit card (Tornbohm , 2017)

- Consumer Loan processing – Most of the consumer loans including Mortgage, involve credit checks and verification. RPA could act as a catalyst to accelerate this process based on defined rules and quicken the process of decision making.

- Fraud detection – RPA can quickly perform if-then analysis on the customer transactions and facilitate financial fraud detection.

3.3.2 B. RPA in Insurance

Insurance companies across the globe are greatly dependent on manual back office processes. This makes it essential for various insurance companies to automate various processes to meet rapid customer growth and improve their processing time. Some of the potential automation processes includes,

- Claims processing – RPA can expedite claims processing by gathering required financial information from various sources and integrating all this disparate information with a high level of accuracy. (Tornbohm , 2017)

- Business process analytics – RPA allows monitoring of every financial task a business executes which gives valuable insights. This insight allows further process improvements and decision making based on insurance terms.

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4. Challenges Faced by Artificial Intelligence in Finance

4.1 Volume

4.1.1 Processing performance:

One of the main challenges faced in computations with Artificial Intelligence and financial data processing is the simple principle that scale, or volume, adds computational complexity. As the scale becomes large, tech operations too, become costly and less accurate. For all the algorithms of Artificial Intelligence, the time needed to perform the computations starts to increase exponentially with the increase in data size and some algorithms may even be rendered unusable for very large datasets. Moreover, as data size increases, the performance of algorithms becomes increasingly dependent upon the architecture used to store and move data. (Zaharia et al., 2012).

4.1.2 Curse of Modularity:

Many AI algorithms assume that the financial data being processed can be held entirely in a single file on a disk. Multiple classes of algorithms are designed on strategies and building blocks that depend on the validity of this assumption. However, when data size fails on this premise, algorithms are affected.

4.1.3 Class Imbalance

As datasets grow larger, the assumption that the financial data is uniformly and appropriately distributed across all classes of the program is often rendered false (Ghanavati et al, 2014). This leads to class imbalance, in which the performance of an artificial intelligence algorithm can be negatively affected when datasets contain financial data from classes with various probabilities of occurrence and unfiltered, incorrect data. (L'Heureux, 2017).

- **Variance and Bias**

Artificial Intelligence in finance relies upon the idea of generalization. Through observations and manipulations of data, representations can be generalized for their analysis and prediction. Generalization error can be broken down into two components: variance and bias - Variance describes the consistency of a learner's ability to predict random things, whereas bias describes the ability of a learner to learn the wrong thing (Domingos, 2012). Therefore, when dealing with Big Data, caution should be taken as bias can be introduced, compromising the ability to generalize.

4.2 Variety:

The main challenge associated with variety in Artificial Intelligence is the locality of Financial Data. AI algorithms assume that the entire dataset is found in memory or in a single disk file. However, in the case of Large amounts of data is present in several different locations. Traditional machine learning practices would first require data to be transferred to the computing location. With large datasets, transfer would result in processing latency and could cause massive network traffic. Consequently, an approach of bringing computation to data as opposed to bringing data to computation has emerged.

4.3 Data Availability

Historically, many Artificial Intelligence approaches have depended on data availability. However, in the context of streaming data, where new data is constantly being generated, such a requirement cannot be met. Moreover, data arriving at non-real-time intervals is prone to pose a challenge. Here, the algorithm does not keep up with arriving data, but instead carries out the already learned task on new data. To accommodate the knowledge embedded in new data, these models must be retrained. Without retraining, they may become outdated and cease to reflect the current state of the system.

4.4 Data Provenance

Data provenance is the process of tracing and recording the origin of financial data and its movements between locations (Grolinger et al 2013). Recorded information, the provenance data, can be used to identify the source of processing error since it identifies all steps, transactions, and processes undergone by invalid data, thus providing contextual information to AI. It is therefore important to capture and retain this financial metadata. However, in the context of Big Data, the provenance dataset itself becomes too large, therefore, while these data provide excellent context to machine learning, the volume of these metadata creates its own set of challenges. Moreover, not only is this dataset too large, but the computational cost of carrying this overhead becomes overwhelming (Wang, 2019).

5. Future Prospects of Artificial Intelligence in Finance

Putting aside the established use cases of machine learning in finance, as discussed in the above section, there are several other promising applications that Artificial Intelligence technology can offer in the future. While few of these have relatively active applications today, others are still at a nascent stage. These include.

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5.1 Artificial Intelligence in Financial Transactions in E-commerce

- Personalized and dynamic pricing and market campaigning of specific products for target customers and particular circumstances.

- Analyzing and predicting payment distribution, trend and growth in terms of different access interfaces and channels, e.g., online, mobile, IoT devices, with different profiles of customers and for various purposes; the learned results could further inform better risk management, surveillance, marketing and recommendations. (Appelbaum, 2017).

5.2 Global and Cross-market prospects of Artificially Intelligent Finance

Global and cross-market analysis refers to the analysis of economic-financial systems, products, services, activities and events in a highly globalized market or across multiple relevant markets.

- Learning the influence of macroeconomic variables and factors on micro-level financial indicators and factors (e.g., an asset price and its movement), and modeling the influence propagation across financial indicators, markets, instruments and companies, e.g., by integrating financial time series analysis, dependence models such as copula with sequential modelers such as recurrent or graph neural models;

- Modeling the couplings between markets, countries, regions and companies, modeling the influence of couplings on their economic, social, cultural, health and political systems, and estimating the impact and consequence of their decoupling;

- Representing and quantifying financial stability, soundness and vulnerability of global economic systems based on indicators of banks, shadow banks, mutual funds, hedge funds, insurance companies, and pension funds and modeling their mutual influence and relations;

- Estimating and analyzing global financial crisis and crisis contagion across companies, banks, financial markets, countries and economic entities by involving financial indicators about these entities and their financial statements, news, and social media information;

- Predicting economic indicators such as the GDP of a country and the world by modeling the influence of significant external, regional and global economic, social, cultural and political events on the indicators;

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5.3 Artificially Intelligent Currency

- Efficiently building trustless, transparent and decentralized oracles in blockchain by involving truthful and multimodal information and controlled gas cost etc. for blockchain optimization;
- Developing privacy-preserving systems, methods and measures for ensuring the privacy preserving in blockchain, and detecting violations of privacy in blockchain businesses;
- Optimizing blockchain systems e.g. decentralization, robustness, efficiency, scalability and security in mixed-type, multimodal and dynamic and uncertain blockchain data and businesses, supporting cross-chain extensions and smart contracts in blockchain businesses;
- Designing smart misbehavior screening algorithms and systems to filter and alert on misbehaviors in blockchain networks and financial activity;
- Designing more efficient and accurate algorithms for discovering cryptocurrency, and predicting the cryptocurrency price and market movement such as by learning relevant opinions and indications from news and social media discussions;
- Recommending and predicting blockchain financing such as initial coin offerings and cryptocurrency portfolios;

Conclusion

Artificial Intelligence in Finance has shown considerable growth, transforming various subfields of finance such as banking, insurance and stock market prediction to produce accurate and precise results post processing mass data. While these developments have shown a multitude of benefits, it is imperative to address the underlying concerns related to Artificial Intelligence technology in Finance. Issues such as security of sensitive financial data, handling the volume of data, access to all potential data and tapping into various data locations are yet to be solved. Future algorithms have to be developed taking the aforementioned concerns into consideration. Therefore, further research is required in areas where challenges are faced by AI in finance so that these issues can be eliminated to produce more accurate predictions. The development of new systems based on current research about challenges and flaws of current systems is also required to shift business transactions and financial activity to a more data specific medium for economic growth and development.

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