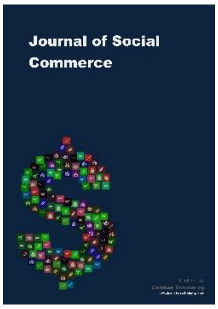

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Applications of Machine Learning (ML) - The real situation of the Vietnam Fintech Market

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Abstract

Machine Learning (ML) is a well-known term in the technological field. However, using ML models in financial institutions is a matter of concern. In fact, the 4.0 Industry has encouraged them to expand their digital system to bring the best experience for their clients. This journal will discuss the definition and applications of ML, the actual situation of the Vietnam Finetech Market. Thereby, we will make predictions about the future of financial institutions, which determines them to use ML in their activities.

Introduction

AI (Artificial Intelligence), or artificial intelligence, is being integrated and integrated into the world of financial services by its ability to perform specific tasks subtly beyond humans, especially when handling unstructured raw data. Machine learning is an area of artificial intelligence that deals with the study and construction of techniques that allow systems to "learn" automatically from data to solve specific problems (Stojanović et al., 2021 The algorithms of this approach are computer programs that can learn how to complete tasks and improve performance over time. Machine Learning is most used in financial services needs because of its data analytics and automation capabilities applied to specific financial transactions. For example, financial analysis, profit margin forecasting are the things that machine learning and artificial intelligence (AI) can contribute to improving productivity, reducing costs, and enhancing the experience. customer experience. Currently, the study of machine learning (Machine Learning), its application and expansion in all aspects of the

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economy is still a hot topic, always receiving a lot of attention from researchers. science worldwide (This article is written with the purposes of synthesizing models and applications related to Machine Learning (ML) (Kumar et al., 2021). Simultaneously, it gives an overview of the Fintech market in Vietnam to bring opportunities to research the use of ML models in Vietnam to the authors.

Literature Review

According to Noor et al (2019), machine learning in finance is defined as a set of learning algorithms and frameworks for financial modelling from data and broadly falls into three branches. Unsupervised machine learning: is a data mining technique for partitioning and reducing the dimension of data. Unsupervised learning augments and generalizes statistical approaches to data reduction, such as principal component analysis. An example of unsupervised learning used in finance is K-means clustering for portfolio selection;

Supervised machine learning is either a parametric or non-parametric, algorithmic or probabilistic method of learning the relationship between repressors and regress ands. Supervised machine learning generalizes statistical techniques such as ordinary least squares (OLS) regression or time series methods such as auto-regressive models. Supervised machine learning assumes that the decisions made by the model are inconsequential to the input. Only a handful of supervised machine learning are suitable for non-stationary data; and

Reinforcement learning is a method of stochastic control, with feedback, which learns a policy based on decisions which do change the state of inputs. Reinforcement learning generalizes stochastic dynamic programming and is likely to be the most impactful for trading and investment management. However, because of its complexity, it is the most under-exploited method in finance. Example applications in finance include derivative pricing, optimal hedging, Merton's portfolio problem and optimal trade execution.

Machine learning is an increasingly key influence on the financial services industry. In this paper, we review the roles and impact of machine learning (ML) and artificial intelligence (AI) on the UK financial services industry. In the UK a new AI start-up has been established on roughly a weekly basis since 2014.4 London is a main hub for AI start-ups, and some of the prominent firms include. Cognition X report, London's role as an AI supplier5 base is twice the size of Berlin and Paris combined. London is also extremely well poised to be an AI and ML leader in finance and insurance, with new supplier formation growing at an annual rate of 42 per cent (compared with the global rate of 24 per cent annually (Pramanik & Jana, 2022).

ML systems comprise five components: (i) a problem, (ii) a data source, (iii) a model, (iv) an optimization algorithm, and (v) validation and testing. The ideal situations for ML are those that require extracting patterns from noisy data or sensory perception. The four main drivers of the growth in ML include: (i) the transition from physical to electronically stored data, (ii) improvements in memory and computing speed, (iii) easier access to data due to the Internet, and (iv) low-cost high-resolution digital sensors (Levantesi et al., 2021; Faisal et al., 2021)

Methods

Authors mainly use experiences, observations, practical situations with cases studies of Fintech market in Vietnam combined with qualitative analysis, synthesis, and explanatory methods. This study also uses historical and dialectical materialism methods, with data and statistics in Vietnam.

Result and Discussion

Machine Learning Models using in Finance

Credit scoring is one of the functions of financial institutions. There are many researches that mention Machine Learning models applied for it and one of them is CART (Classification and Regression Trees). It is used as a discrimination tool (Allen, & Jagtiani, 2021) used to analyse CART in credit scoring in their research about the Default Predictors and Credit Scoring Models for Retail Banking. In this journal, they found out some advantages of using CART in credit scoring such as being intuitive, easy to explain to management and able to deal with missing observations (Thanh, 2021).

They concluded that CART can produce successful models and be more efficient to discriminate between low-risk and high-risk clients. On the other hand, CART can not only classify credit customers, but also it can be used for predicting. We can build a decision tree to predict loan approval on age, credit rating, salary and various other variables.

SVM model (Supporting Vector Machine)

SVM (Supporting Vector Machine) is linear. It is more prominent than other models because it can deal with classification problems using SVM classifier and regression problems by SVM repressor. However, the SVM classifier is the backbone of the SVM model, which is the most suitable algorithm for classification problems (Kowalewski & Pisany, 2020).

As a linear algorithm, SVM's core can be imagined almost like a Linear or Logistic Regression. For example, SVM classifier creates a line (plane or hyper-plane depending on the dimension of the data) in an N-dimensional space to classify data points that belong to two separate classes. The original SVM classifier has this target and was originally designed to solve binary classification problems. However, unlike the assumption that linear regression is the most suitable and the best concept of line, which is the predictive line that gives the minimum Sum of Squared Error (using OLS Regression), or Logistic Regression that use Maximum Likelihood Estimation to find the best fitting sigmoid curve, SVM is uses the concept of Margins to come up with prediction.

Application of Machine Learning in Finance

Credit scoring

Dang et al (2021) stated that: "The process of modelling creditworthiness made by financial institutions is called credit scoring". This process involves collecting, analysing, and categorizing credit variables to evaluate credit decisions. Credit scoring is an important stage in the risk management process of financial institutions and banks. A good credit score helps make the credit quality better, thereby enhancing the competition and profitability of banks and financial institutions.

As for the traditional credit scoring models, potential borrowers must have sufficient credit information. This approach greatly depends on the subjective opinion of the credit officer. Due to the lack of staff's appraisal level or the collusion between staff and customers, banks have to cope with many risks. Hence, a credit score cannot be calculated without information, and a potentially trustworthy borrower is likely to be unable to access credit and develop a credit history with banks (Agarwal et al., 2021).

Currently, commercial banks have been applying machine learning algorithms to help develop creditworthiness and willingness to repay loans; hence, by using credit scoring models, lenders can decide whether to grant or deny credit to applicants. In particular, a credit scoring model is a method that quantifies the level of risk by estimating the rating scale, which is applied diversely for each type of customer. Credit rating tools that use machine learning are designed to speed up lending decisions and minimize risk. Simultaneously, machine learning algorithms have enabled a larger, faster and cheaper quality segment of borrowers, helping to facilitate better access to credit.

The objective of the credit scoring model is to categorize credit applicants into two classes: a “good credit” class that is responsible for repaying financial obligations, and a “bad credit” class that is denied to grant credit due to a high probability of default. This classification depends on sociodemographic characteristics of the borrower, such as age, education, occupation, income, previous loan repayment status, and loan type.

Asset pricing is the study of the value of claims to uncertain future payments. There are two key factors involved in valuing assets, including the timing and the risk of payments. While the effects over time are quite easy to explain, the risk corrections are far more important. For example, U.S. stocks have a real return of nearly 9% on average over the last 50 years. Only about 1% is due to interest rates; the remaining 8% is a premium for holding risk. Hence, the fundamental goal of asset pricing is to know the behaviour of risk premiums; however, risk premiums are very difficult to measure. Botchey et al (2020) give three main reasons why investors prefer machine learning methods in asset pricing.

First, asset valuation is the practice in which investors predict the risk premium of the asset being valued. Machine learning method is one of the best ways to forecast an event in general and the risk premium of an asset in particular. Second, asset pricing requires a large number of inputs that sometimes have a very high correlation, which reduces the pricing power. Machine learning can deal with this problem by selecting key variables in valuing each asset, thereby improving the predictability of asset valuation. Third, traditional empirical methods of asset pricing by means of regression often have difficulty in identifying regression models. This problem can be completely solved by machine learning methods. In particular, machine learning provides a wider list of potential predictor variables and richer specifications of functional form. This solves the problem of risk premium measurement and enables a more reliable research of the economic mechanisms of asset pricing.

In addition, the benefit of machine learning in asset pricing is to help value assets that are illiquid and may not be similar to other assets (if two assets are similar, their prices may be similar). In this case, traditional valuation methods, such as discounted cash flows or comparable, often have multiple valuation ranges, making it difficult to determine asset prices.

Fraud Detection

Machine learning can be ideal for fraud detection as it can process large amounts of data including transactions patterns and methods of customers. The analysis process of ML is quick and efficient which helps reduce time to detect abnormal behaviours and also limits losses. In addition, ML is beneficial for financial institutions thanks to its ability to improve accuracy since “human error in recording or analysing data is eliminated from the equation” (Morgan, 2022). The model will produce better projections as long as there is more data for the model to learn.

One method of ML that can be applied to prevent and identify fraud is unsupervised ML, for example, clustering and classification. An example of fraud is email phishing which is a way that a person attempts to access accounts with personal data by deceiving responders into replying to emails with their information. ML models can prevent this by studying some aspects of an email and categorizing them into good or spam.

Other frauds ML can prevent are payment fraud and credit card theft. The thief will steal information to conduct transactions (online transactions, for example). ML models have the ability to identify unusual activities as they will study customers' previous purchase information such as amounts, locations, and types. By using ML models, financial institutions can avoid cyber-attacks. The models include three stages: detect patterns with clustering models (unsupervised learning), assess the patterns to determine the likelihood of cyber-attacks (labelling), then train the models (supervised) to immediately forecast attacks.

Vietnam Fintech Market executive summary

Fintech stands for financial technology, is used for describing new tech that seeks to improve and automate the delivery and financial services. The digital technology with 4.0 Industry has created favourable conditions to enhance financial activities, which contributes to the finance-banking sector. Recognizing the importance of the technology field in the future, the State Bank of Vietnam has licensed the establishment of Fintech companies since 2008. The appearance of Fintech companies has brought various positive changes for Vietnam's banking system and strongly influenced the development strategies and business approaches of traditional financial service providers. After many years, the Vietnam Fintech Market has had more and more progress and we can summarize some main features of it (Mosavi et al., 2020).

Features

According to the Fintech News Singapore report, the number of Fintech companies in Vietnam tripled in the 2017 - 2020 period. Due to the great evolution and investors' attraction, there was a fivefold increase in this number, from 40 companies in 2016 to about 200 companies in 2020. Fintech transaction market has reached nearly 9 billion USD (Nguyen et al., 2021). In 2019, according to the Global Fineable ranking report, Vietnam reached 51st, which encouraged the development of the Vietnam Fintech market because this is a new segment in Vietnam. However, Vietnam has a potential Fintech market and there is an upwards trend in the number of Fintech companies.

Table 1. presents the Fintech Points ranking in 2019

Nation	Point	Rank
America	31.789	1
England	23.262	2
Singapore	19.176	3
South Korea	11.543	18
China	11.143	21
Japan	11.114	22
Malaysia	9.692	36
Thailand	9.415	39
Philippines	8.831	46
Indonesia	8.658	47
Taiwan	8.321	50
Vietnam	8.118	51

Currently, the Fintech sector in Vietnam has mostly focused on two areas: payment and peer-to-peer lending (P2P lending). In addition, a number of areas, such as insurance services, securities, and so on, are still in their infancy. According to statistical data from Fintech News 2020, among Fintech services in Vietnam, payment activities account for the highest proportion with 33%, followed by P2P with 15.5%. The Vietnamese government encourages individuals to convert to electronic payments instead of cash to foster the development of a cashless economy, which makes online payment attract Fintech businesses. Electronic payments are also being increased as a result of the Covid-19 outbreak, and Vietnam is also a densely populated nation with a large number of individuals utilizing cell phones and the

Internet (Soni et al., 2022). This trend is expected to continue, with the value of mobile payments in Vietnam expected to reach 70.9 billion USD in 2020, an increase of over fourfold over the previous year, according to the SBV. the year 2016 (ISEV 2020).

Currently, the five biggest e-wallets in Vietnam are MoMo, Payoo, Moca, Zalo Pay và Viettel Pay (Saka et al., 2021). In particular, Viettel has launched the “4.0 Market” in Da Nang. The buyers and sellers can exchange goods without cash or Internet, they will use Viettel Money. This is a new model market in which they all use Viettel subscribers, and are gradually gaining access to digital financial services through the use of Viettel Money. As a comprehensive digital financial and commerce ecosystem with the nucleus of Mobile Money, Viettel Money allows people to carry out transactions of buying, selling, transferring money, making payments, etc., instead of cash. quickly and safely. This is a breakthrough of Viettel in advancing digital payment (Abbasi et al., 2021).

Aside from payments, the number of service providers in the sector of peer-to-peer lending is rapidly increasing. According to a survey conducted by the State Bank of Vietnam in 2019, Vietnam has over 40 firms providing peer-to-peer lending services, with many of them originating in China, Indonesia, and Malaysia. The increase in numbers of P2P lending firms in Vietnam is a symptom of the country's burgeoning Fintech sector. However, there is presently very little trustworthy data on the loan size, total loan amount, or growth rate of this type of Fintech organization.

Fintech's operations in the payment sector are governed by the 2010 State Bank Law, non-cash payment decrees, and payment intermediary services guiding circulars. As a result, Fintech's payment operations are classified as offering intermediate payment services and require a State Bank license to operate, such as e-payment gateway and e-wallet services, among others. In addition, the fundamental standard "QR Code technical specification shown from the acceptor's side" is stated in Decision 1928/QD-NHNN dated October 5, 2018 on the form of payment through QR Code. receive payments in Vietnam".

Besides, the Government/SBV also creates a lot of room for financial technology activities in general to develop. For example: Circular 09 of the State Bank dated October 21, 2020 allowing third parties to provide cloud computing services effective from January 1, 2021; Circular No. 16 of the SBV dated December 4, 2021 allowing individuals to open payment accounts by electronic method (eKYC) effective from March 5, 2021; Decree 37 of the Government dated March 29, 2021 allowing credit institutions to connect to the national population database, effective May 14, 2021; Decision No. 810/QDNHNN dated 11/5/2021 promulgating the Plan on digital transformation of the banking sector up to 2025, with orientation to 2030; Decision 942/QD-TTg dated June 15, 2021 assigning the State Bank to assume the prime responsibility for researching, building and piloting the use of virtual money based on block chain technology (Kowalewski et al., 2021).

Limitations

In 2020, Vietnam will have 141 Fintech businesses, which is the lowest number among the ASEAN-6 countries (Indonesia – 557, Malaysia – 407, Philippines – 212, Singapore – 1200, Thailand – 227). The survey report of the State Bank of Vietnam in 2019 shows that the majority of Fintech companies in Vietnam are newly established companies with a small scale. Specifically, about the development stage of Fintech companies in Vietnam, 44.2% of Fintech companies are in the stage of starting business activities, but the break-even point has not yet been reached; 26.4% are in the minimum viable product launch (MVP) stage and have sales in the last six months to the time of the survey; 11.76% has reached the breakeven stage; 2.94% are in the proof-of-concept stage but no revenue yet; 8.82% achieved profit; 5.88% are in the business model development stage.

According to the Zabala & Ślusarczyk (2020). survey report, the majority of Fintech companies in Vietnam are tiny, newly founded businesses. In terms of the development stage of Fintech firms in Vietnam, 44.2 percent of Fintech companies are in the process of establishing business operations, but have not yet reached the break-even point; 26.4 percent are in the MVP stage and have had sales in the six months prior to the survey; 11.76 percent have reached breakeven; 2.94 percent are in the proof-of-concept stage but have yet to generate revenue; 8.82 percent have made a profit; and 5.88 percent are in the business model development stage.

In Vietnam, there are few appropriate institutes offering training that includes both technology and finance (Hoang et al., 2021), in Vietnam, understanding of emerging technologies such as application programming, artificial intelligence, block chain, big data, and so on is not widely spread. As a result, a large number of jobs and titles will be handed to foreigners rather than Vietnamese human resources. According to Vietnamworks ITECH, by the end of 2019, Vietnam will be short roughly 80,000 IT human resources compared to demand. Vietnam will be short of over 400,000 IT personnel by 2020, according to the Ministry of Information and Communications.

The trend of cooperation between Fintech and Banks in Vietnam

Fintech is a new sector in Vietnam. Although it has advantages of technology, creative ideas, and flexibility in the organization, it has a lack of experience in the Finance-Banking field, and its brand and reputation are not big enough to easily expand in Vietnam. On the other hand, the great innovation of Fintech companies has certainly created many challenges to traditional banks currently. In the future, they cannot completely replace banks, but they have made significant impacts on the business models of banks, especially in the payment segment (Moro, 2021) The rapid spread and complicated evolution of covid-19 has changed the payment methods of consumers.

Many experts suppose that Coronavirus exists on the surface of money paper and spreads diseases, WHO also recommends that consumers should avoid using cash and convert to use cashless or non-cash payments, which has spurred the adoption of electronic payment methods by citizens. Additionally, electronic payment is now not only provided by banks, but also expanded to Fintech companies, so consumers will have various choices with many attractive incentives. According to statistics of the State Bank of Vietnam, also in the first 9 months of 2020, the number and value of non-cash payment transactions both increased strongly, 75.2% and 30% respectively over the same period last year; especially, the number and value of transactions via mobile phone channel increased sharply, by nearly 125% and 130% respectively over the same period in 2019.

Besides, the Vietnam banking sector is upgrading the global trend to build a digital banking model, which enhances the process of transforming core banks, advanced technological equipment and digitizing assets (Nguyen et al., 2021). Therefore, in order to implement this model, it is essential to cooperate with Fintech companies, so that traditional banks and Fintech firms can coordinate in the development of banking products and services. According to statistics of the State Bank, 72% of Fintech companies have cooperated with banks in Vietnam to provide products and services, only 14% develop new services and 14% are ready to compete with banks. The reality in Vietnam shows that most banks now sign up with a few Fintech companies to provide payment and money transfer services to customers such as money transfer service on mobile phones (smartphones).

Military Joint Stock Commercial Bank - MB cooperates with Military Telecommunications Group - Viettel to implement; Vietcombank cooperates with M-Service Online Mobile Services Joint Stock Company to implement a small value money transfer service based on the MoMo e-wallet platform. Currently, most banks are associated with Momo wallet to develop e-wallets; VPBank cooperates with VnPay, Bankplu to promote payment and online banking transactions; VietinBank cooperates with seven Fintech companies to bring customers outstanding financial technology products (Nguyen, 2020). In the period 2018 - 2020, in addition to cooperation deals between banks and Fintech, the Vietnamese market also recorded a series of cooperation deals within the Fintech industry such as Grab. Or most recently, in November 2020, Grab Vietnam and Lazada Vietnam announced a partnership to integrate the two companies' services on their respective platforms.

Table 2. presents the Cooperation model of banks and Fintech in Vietnam

Cooperation model	**Organization**	**Description**
Banks and Fintechs provide a certain type of service	VPBank and Timo	Provide e-banking services
	VPBank and Moca	Provide digital payment services
	VIB and Weezi	Application for transferring money via social networks (MyVIB Keyboard)
	Techcombank and Fastacash	Money transfer feature via Facebook and Google + on F@st Mobile app
	Vietcombank and M_Service	Remittance payment
	VietinBank and Opportunity Network	Providing a platform for connecting businesses as customers of VietinBank with more than 15,000 businesses in 113 countries that are members of ON, creating effective market expansion opportunities for domestic businesses with partners. foreign.
	MB and Viettel	Allows users to make transactions in Facebook's Messenger app
	CIMB and Toss	Issuing prepaid virtual cards on Toss app (Customers can apply for cards on non-bank platforms)
Fintech acquires a bank subsidiary	Lotte Card buys Techcom Finance (belonging to Techcombank)	Expanding consumer lending activities in Vietnam
Fintech Investment Bank	UOB Venture Management (UOB) and TheBank	TheBank, Vietnam's financial comparison platform, received a $5 million investment in UOB's Series A funding round.

Proposing cooperation solutions between Fintech and credit institutions

Platform as a Service (PaaS): PaaS model has been developing currently. Therefore, banks can rent Fintech's platform solutions to use for their clients, simultaneously, sharing revenue with Fintech firms instead of investing. This model can bring long term development, win-win and reduce risks. PaaS platforms that Nexttech can provide such as mPoS/SmartPos, Merchant Platform, Online/Offline instalment conversion portal for banks, and Next360 comprehensive digital conversion platform. Conversely, banks can also provide some PaaS services for Fintech companies such as Credit Score service system, financing for Micro SMEs to develop together and serve customers better.

Developing user ecosystem: Diversifying services for End users onto the Bank's Mobile Banking system such as: Top Up phone, payment for electricity, water, financial bills, collection of tuition fees, securities, etc. At the same time, bringing banking services to Fintech's Mobile app and Supper app platforms such as opening cards/accounts online, saving online, accumulating loyalty points, etc.

Prioritize the development of information infrastructure: According to Eggert et al. (2014), revenue and profit will be redistributed towards banks that are successful in applying digital technology to automate processes and create new product, improve regulatory compliance, enhance customer experience, and create new value chains. Building digital capabilities is the main focus of the bank in digital transformation to keep up with new trends and not be left out. Digital competence is reflected in the following six aspects: (i) Data-driven governance

(ii) Personalization of customer experience; (iii) Digital Marketing; (iv) Streamlining and digitizing banking processes; (v) Application of new generations of technologies; (vi) Restructure the organization and change the decision-making mechanism to support the digital environment. To exploit the strengths of the banking system, Fintechs and promote the effectiveness of the combination of Fintech banks but still ensure national financial security, a common data centre is required.

The National Credit Information Centre (CIC) has aggregated and shared customer credit history information that has ever transacted at commercial banks. However, the bank operates with a variety of financial services, not just providing credit. Especially when the bank changes its business model from a traditional banking model to a digital banking model and an open banking model by linking with a 3rd party providing services. financial services to individuals and organizations in the economy.

Therefore, there is a need for a common database centre between banks and Fintech companies in the financial sector in order to effectively exploit information sources on the one hand, and on the other hand, to make data sources transparent to avoid risks. Risks due to asymmetry of information for banks- Fintech when choosing partners as well as coordinating financial-monetary business. In order for the common data centre to have a reliable and rich source of data, when developing a project to establish a common data centre (in addition to the current CIC customer credit data), it is also essential to issue an open data standard. Information from the open data centre will create a level playing field for banks in accessing digital technology 4.0 through self-development of digital systems or cooperation with Fintechs while still ensuring financial security. national government.

Conclusion

In the 1990s, Bill Gates had a famous quote about banks, which stated. We need banking, but we don't need banks anymore." Compared with the summary of the Vietnam Fintech Market that we mentioned, it is clear to see that Fintech companies are growing fast and having a lot of breakthroughs because they can provide various financial services, which can make them replace the role of financial institutions in the future. Therefore, banks and others will become less competitive than Fintech companies, which encourages financial institutions to modify their activities by applying technology. Machine Learning is one of effective tools for them to choose. Hence, considering using ML models is definitely essential for financial institutions because it relates to the existence of them in the future.

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