The University of Hong Kong

FITE4801 Final Year Project

AI-based Real-time and Early Detection of Financial Institution Vulnerabilities in Hong Kong

Project Plan

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1 Background

1.1 Supervisory technology and the adoption in Hong Kong

Supervisory technology ("SupTech") is an emerging area of financial technology ("FinTech") where regulatory authorities harness cutting-edge technologies to enhance their capabilities in supervising financial institutions (Financial Stability Board [FSB], 2020). Its increasing significance can be traced to the growing attention towards effective supervision in meeting the increasing regulatory expectations after the 2008 global financial crisis (Dordevic et al., 2021). Since then, regulators have called for more data reporting and risk assessment programs to detect potential vulnerabilities (Dordevic et al., 2021).

Meanwhile, as SupTech provides a range of analytical tools like artificial intelligence ("AI") and machine learning ("ML") which can process a multitude of data to identify key risk patterns, more regulators have started to adopt SupTech in their supervisory frameworks (European Securities and Markets Authority [ESMA], 2019; FSB, 2020). In particular, the Hong Kong Monetary Authority ("HKMA") published a newsletter relating to its adoption of SupTech in 2021 (Hong Kong Monetary Authority [HKMA], 2021). The newsletter sets out a 3-year roadmap of adopting SupTech which consists of three main phases deploying different technologies (HKMA, 2021). Ultimately, the roadmap aims to explore the uses of advanced technologies in complementing the current supervisory framework (HKMA, 2021).

At present, the HKMA implements a risk-based supervisory framework with an integration of the CAMEL rating system which has been adopted for nearly thirty years (HKMA, 2022). It encompasses five key elements: Capital adequacy (C), Asset quality (A), Management (M), Earnings (E), and Liquidity (L) (HKMA, 2022). These elements reflect the risk profile of a financial institution, which will be rated at a scale of 1 to 5 by the regulator (HKMA, 2022). To assign a CAMEL rating for a financial institution, the HKMA will firstly assess the risk profile that is established through a series of ongoing processes including on-site examinations, off-site supervision, prudential meetings, etc. (HKMA, 2022) After all, the CAMEL rating acts as a forward-looking tool, enabling the HKMA to detect vulnerabilities which could jeopardize the stability of the banking system (HKMA, 2022).

1.2 Problem statement

However, there are still some limitations in the current supervisory framework which may hinder regulators from achieving the supervisory objectives. Apparently, the risk assessment method adopted by the HKMA in the supervisory framework, while comprehensive, is nonetheless a long and tedious process. With numerous interviews, meetings and on-site and off-site examinations in place, it may take months or even a year to run a complete cycle of risk assessment. The inability to produce results in a timely manner lowers the forward-looking capabilities of HKMA, which may result in a delayed response to potential financial problems. Worse still, the adoption and development of SupTech solutions in Hong Kong is very limited. The rising trend of new business forms and the vast amount of data created each day calls for regulators to incorporate SupTech solutions into their regulatory framework for more effective regulation. While the HKMA has set out to develop its own SupTech strategy in the 3-year roadmap, they are still in the initial stages of this journey (HKMA, 2021).

2 Objectives and Scope

To address the supervisory problems as mentioned, this project aims to develop a SupTech application using machine learning and natural language processing (NLP) techniques etc. The application will provide real-time detection and forecast of financial risks in financial institutions in Hong Kong. Its main components are as follows:

1. **Real-time financial data monitoring**
   The web-based dashboard provides an overview of the current financial performance of each financial institution with the most up-to-date financial data, enabling real-time monitoring and early detection of financial risks.

2. **CAMEL-based risk profile prediction**
   With the use of machine learning techniques, hidden patterns can be identified from historical data, producing more accurate and objective forecasts of risk profile for the CAMEL rating. This allows regulators to anticipate financial problems before they arise, thus further enhancing their forward-looking capabilities.

3. **Relative vulnerability index**

   Within each subgroup, the relative vulnerability index (RVI) of financial institutions is calculated, providing insights into the relative risk of the financial institution as compared to its counterparts in the same subgroup. This facilitates quick comparison within subgroups and easy identification of more at-risk financial institutions.

The target audience of our SupTech application are the Hong Kong regulators. Our goal is to assist them in risk assessment with faster results, real-time updates and forecasts. A successful final product would be helpful in refining the current supervisory framework in Hong Kong and hence close regulatory gaps.

3 Methodology

3.1 CAMEL-based risk profile prediction

3.1.1 Time-series analysis

As mentioned earlier, the risk profile of a financial institution is incorporated into the CAMEL rating for early detection of vulnerabilities (HKMA, 2021). Yet, recent research on risk assessment of financial institutions mostly focuses on predicting financial ratios which represent two of the elements in CAMEL, i.e., capital adequacy and liquidity (O'Keefe, 2022; Park et al., 2021; Petropoulos et al., 2019). To expand the scope for a more comprehensive risk profile prediction, we will select a widely used financial ratio ("representative ratio") to assess each element of CAMEL quantitatively. Hence, we expect five time-series models to be employed for predicting the representative ratios. The models would include the traditional autoregressive model and the long short-term memory model. As an illustration, the equation of a time-series model with a 1-year time lag can be formulated as follows:

$$Y_t = \beta_0 + \beta_1 X_{t-1} + a_t$$

where the explanatory variables X_{t-1}, i.e., representative ratio of a CAMEL element, macroeconomic indicators and market sentiment score in the previous year, will be used to forecast the dependent variable Y_t, i.e., the representative ratio in the current year.

3.1.2 Data collection

To collect data for the dependent variable, we will utilize Moody's Analytics Orbis Bank Focus, a comprehensive global database of banks provided by Bureau van Dijk (Moody’s Analytics, 2023). It offers an extensive range of financial statements and regulatory data from various sources (Moody’s Analytics, 2023). With this database, we will collect data from a sample of 6,018 banks over the past 30 years. These banks are selected from jurisdictions including Canada (109 banks), China (265 banks), Hong Kong (60 banks), Singapore (11 banks), and the United States (5,573 banks). Notably, these jurisdictions all have sound banking supervisory framework and consistent implementation of the global standards, based on their high-level compliance with the Basel core principles of effective banking supervision and the Basel III framework (Bank for International Settlements [BIS], 2023; Garcia & de Mendonça, 2023). Thus, it is assumed that the sampled banks are subject to comparable supervisory frameworks. Consequently, this results in a total of 50,114 bank-year observations[1] for regression and machine learning analyses.

As for data collection of the explanatory variables, the macroeconomic data, e.g., GDP, inflation rate, stock market index, etc., will be sourced from central banks of regions where the financial institution situates, and the source of data relating to market sentiment will be retrieved using NLP techniques where details will be discussed in the following section.

3.1.3 Computation of sentiment scores using natural language processing (NLP) techniques

Sentiment towards financial institutions needs to be extracted from various text sources, such as news articles and social media posts. Titles and descriptions of news articles about financial institutions will be retrieved from News API, a REST API which collects current and historic news articles from more than 80,000 publishers worldwide (News API, 2023). Social media posts regarding financial institutions will be sourced from X (formerly Twitter) and Reddit, using their respective APIs.

[1] This is subject to change as it depends on the availability of the data on the selected representative ratios.

The sentiment reflected in each piece of text data will be computed in different methods depending on its nature:

1. News articles will be given a sentiment score through dictionary-based sentiment analysis in Python, using the latest (2022) edition of the Loughran-Mcdonald Master Dictionary (Loughran & McDonald, 2010) for score assignments. The score will be normalized to a range of [-1,1].
2. Social media posts will be scored using Natural Language Toolkit (NLTK)'s (a popular Python module for NLP) VADER submodule, which is a rule-based NLP model catered towards weblogs and social media (Hutto & Gilbert, 2014).

The sentiment scores from each piece of text data regarding a financial institution will form an aggregate sentiment score for the financial institution, by taking the arithmetic mean of the individual scores. The arithmetic mean was chosen over the geometric mean for computational ease and accuracy, as all scores will be represented as floating-point numbers between -1 and 1.

3.1.4 Feature selection using regression

Careful selection of explanatory variables is crucial in the model training process (Cai et al., 2018). A common method is to employ a regression analysis to identify the explanatory variables, i.e., the macroeconomic indicators and financial ratios, as well as their lag variables, that hold statistical significance in relation to the dependent variables. The p-value associated with each variable will be carefully examined as a means of filtering the variables. Specifically, a significance threshold of $p < .05$ will be adopted, ensuring that only variables demonstrating a statistically significant relationship with the explained variables are retained for further analysis.

3.1.5 Risk profile prediction using autoregressive model

The collected and processed data will be utilized as the inputs for each of the five autoregressive models. It is worth noting that 70% of the data in chronological order will be used for training, and the remaining 30% will be used for testing. The evaluation metric for this model will be the mean absolute percentage error (MAPE) given its simplicity and scale-independence of different time series.

3.1.6 Risk profile prediction using long short-term memory (LSTM) model

The collected and processed data will be fed into five LSTM models, one for each CAMEL ratio. LSTM is an extension of the recurrent neural network (RNN) designed to better identify long-term dependencies (vulnerabilities in this application) in the data. Over many steps (time periods in this case), RNNs typically experience either the exploding or vanishing gradient problem, which may lead to unstable, oscillating weights in the network or unacceptable training times (Staudemeyer & Morris, 2019). The LSTM network employs a constant error carousel, ensuring that errors (gradients) are passed through each memory cell (Staudemeyer & Morris, 2019).

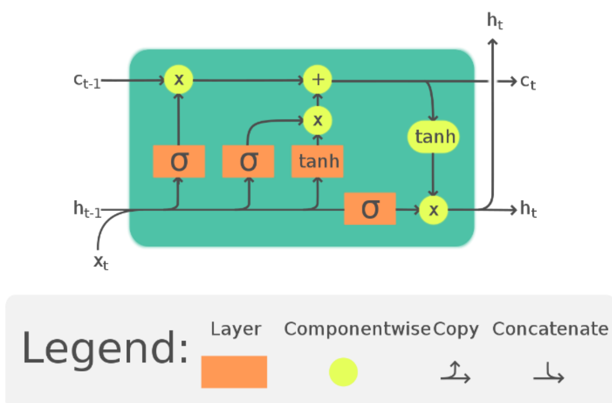

Figure 1: Structure of an LSTM memory cell. Each cell is made up of a forget gate to drop irrelevant memory, an input gate to add new memory, and an output gate to pass the new memory onto the next memory cell.

The model will be trained using batches of data, with each batch containing time-series data for a single financial institution. For each time series, the chronologically oldest 75% will be used for training, and the latest 25% will be used for validation. 10% of the institutions' data will be set aside to test the model after training.

During testing, the model's prediction accuracy will be evaluated using the mean squared error (MSE) between the predicted and actual representative ratio. Mean squared error was chosen for its ability to identify big prediction errors by magnifying them, allowing future training steps to eliminate them. The results of the model will then be compared with that of the AR models (Section 3.1.5) to determine whether the deep learning model provides genuine benefit over current methods.

3.2 Relative vulnerability index for early detection

Finally, to derive a standardized measure like the CAMEL rating, we will construct a RVI on a peer-group basis as suggested by some research papers (Ong et al., 2013; Wong & Wei, 2023). We will start with creating several peer groups, e.g., large banks, medium-sized banks, and small banks, based on indicators like total asset size. Although the research papers assumed a normal distribution of those financial ratios, for better approximation, we will evaluate the normality of the distribution of the representative ratios within each group using statistical tests such as the Shapiro-Wilk test (Khatun, 2021; Ong et al., 2013; Wong & Wei, 2023). If the distribution exhibits normality, we will adopt the Z-score approach proposed by Wong and Wei (2023). Each ratio can be transformed into a standardized normal distribution using the mean and standard deviation of the peer group's distribution (Wong & Wei, 2023). An overall RVI can be computed like the Altman Z-score which is a summation of the Z-score of each representative ratio:

$$\text{Standardized RVI} = Z_{C,t}+Z_{A,t}+Z_{M,t}+Z_{E,t}+Z_{L,t}$$

On the other hand, if the distribution does not demonstrate normality, we will instead use an empirical distribution. Since the empirical distribution cannot be standardized, the RVI will be adjusted as:

$$\text{RVI} = \beta_1 C_t+\beta_2 A_t+\beta_3 M_t+\beta_4 E_t+\beta_5 L_t$$

In which the following properties are expected:

1. The mean of the RVI should be 50 out of the scale of 100.
2. The RVI can be viewed as, or at least similar to a normal distribution.

With this construction method, we will predict the future RVI by using two approaches:

1. **Two-step approach**: predict the representative ratios with the superior model (Section 3.1.5, 3.1.6), and input the predictions into the formula to obtain the forecasted RVI.

2. **One-step approach**: implement the long short-term memory model to predict future RVI with the same time-series data in the first approach, except that past RVI data are used in lieu of past representative ratio data. Notably, percentages of training, evaluation and testing data will be identical to that of Section 3.1.6, and the evaluation metric will also be MSE for a fair test between this model and the models in Section 3.1.6.

The end goal is to evaluate whether the deep learning model in the one-step approach can provide better prediction accuracy of the RVI as compared to the two-step approach.

3.3 Web application

3.3.1 Frontend development: dashboard

The web-based dashboard displays key financial metrics for each financial institution, including predicted representative ratios, RVI, and visualizations of the aforementioned in the form of line graphs with respect to time. Recent news headlines regarding the financial institution containing the highest positive/negative sentiments will also be shown. The dashboard will be written in React, a JavaScript library tailored for frontend development.

3.3.2 Backend development

The backend of the dashboard application is split into two parts: the server, and the database. The server is the primary interface for the application frontend to interact with, and will manage various tasks for the frontend, like retrieving data from the database, performing calculations, and storing static assets like images. It will be implemented using Express.js, a Node.js library for server implementations, for its flexibility and simplicity. The database will be used to store data for the application, including input numerical data and text data for machine learning, outputs and weights of the NLP/LSTM models. It will be implemented using MongoDB, a document-oriented database that is flexible and easily connected with the JavaScript-based server and Python-based machine learning programs.

4 Project schedule

In our research project, the data collection, processing, and variable selection phases will commence in early October. Subsequently, the primary training process for the machine learning model is expected to commence in late October, with an estimated duration of four months. The development of the frontend deliverables is planned for January 2024, coinciding with the drafting of the interim report. The final report is anticipated to be finalized in April 2024. A visualization of the proposed project schedule is presented in a Gantt chart (Figure 2) where further details are listed in Table 1 below.

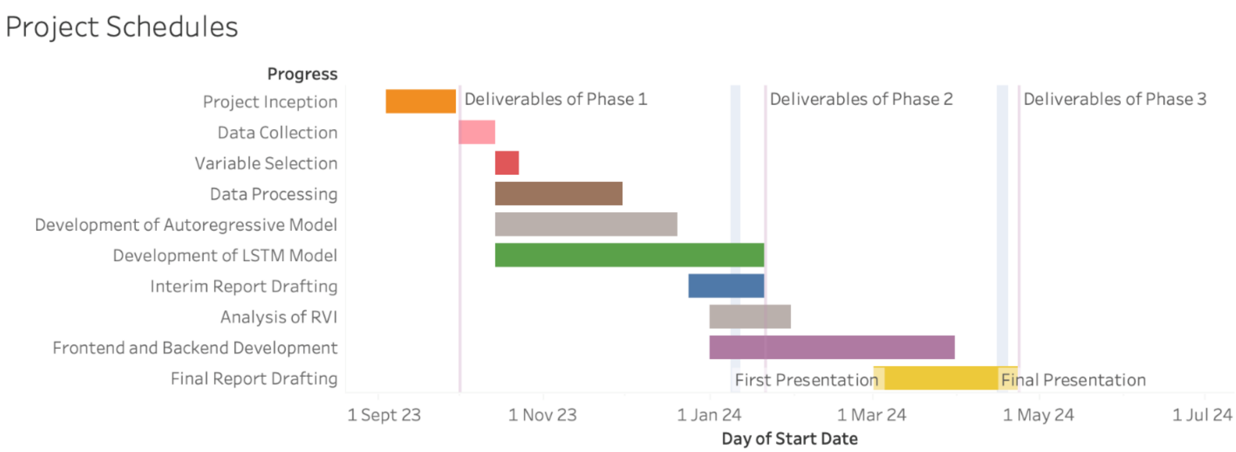

Figure 2: Gantt chart of the project schedule

Schedule		**Milestone** (estimated number of learning hours)	
		Phase 1: Project inception	
2023	Sep	• Literature review (2) • Feasibility assessment (5) • Project plan formation (15)	**Deliverables**: Detailed project plan + website
		Phase 2: Project elaboration	
	Oct	• Data collection (structured and unstructured data) (10) • Data processing (NLP and RVI method on past ratio data) (10) • Autoregressive model preparation (10) • LSTM model preparation (10)	
	Nov	• Data processing (NLP and RVI method on past ratio data) (15)	

		• Feature/variable selection (15) • Autoregressive model training (15) • LSTM model training (25)	
	Dec	• LSTM model training and testing (15) • Autoregressive model training and testing (15) • Interim report drafting (10)	
2024	Jan	• LSTM model evaluation (10) • Analysis of RVI (10) • Dashboard design (10) • Interim report drafting (5)	**First presentation** **Deliverables**: Prototype + interim report
Phase 3: Project construction			
	Feb	• Model fine-tuning (5) • Analysis of RVI (5) • Frontend and backend development (15)	
	Mar	• Frontend and backend development (10) • Debugging and code documentation (5) • Final report drafting (20)	
	Apr	**Final presentation** **Deliverables**: Finalized product + final report **Project exhibition**	

Table 1: Details of the project schedule

References

Bank for International Settlements [BIS]. (2023, July 23). *RCAP jurisdictional assessments: Regulatory implementation consistency*. https://www.bis.org/bcbs/implementation/rcap_jurisdictional.htm?m=3060

Cai, J., Luo, J., Wang, S., & Yang, S. (2018). Feature selection in machine learning: A new perspective. *Neurocomputing, 300*. 70-79. https://doi.org/10.1016/j.neucom.2017.11.077

Chevalier, G. (2018). *LSTM Cell. Wikimedia Commons*. Retrieved September 23, 2023, from https://upload.wikimedia.org/wikipedia/commons/9/93/LSTM_Cell.svg.

D'Andrea, A., Ferri, F., Grifoni, P., & Guzzo, T. (2015). Approaches, tools and applications for sentiment analysis implementation. *International Journal of Computer Applications, 125*(3), 26–33. https://doi.org/10.5120/ijca2015905866

Dordevic, L., Ferreira, C., Kitonga, M., & Seal, K. (2021). Strengthening bank regulation and supervision: National progress and gaps. *Departmental paper series, 21*(5). 5-10. https://doi.org/10.5089/9781513566658.087

European Securities and Markets Authority [ESMA]. (2019). *ESMA report on trends, risks and vulnerabilities*. https://www.esma.europa.eu/sites/default/files/library/esma50-report_on_trends_risks_and_vulnerabilities_no1_2019.pdf

Financial Stability Board [FSB]. (2020, October 9). *The use of supervisory and regulatory technology by authorities and regulated institutions: Market developments and financial stability implications*. https://www.fsb.org/wp-content/uploads/P091020.pdf

Garcia, M. T. M., & de Mendonça, F. C. (2023). Compliance with the Basel core principles and supervisory structure: A cross-country analysis. *Central Bank Review*, *23*(2). 1-15. https://doi.org/10.1016/j.cbrev.2023.100117

Hong Kong Monetary Authority [HKMA]. (2021, June). *HKMA's adoption of supervisory technology*. https://www.hkma.gov.hk/media/eng/doc/key-information/guidelines-and-circular/2021/20210617e1a1.pdf

Hong Kong Monetary Authority [HKMA]. (2021, July 23). *Guide to Hong Kong monetary, banking and financial terms*. Guide to Hong Kong Monetary, Banking and Financial Terms. https://www.hkma.gov.hk/eng/data-publications-and-research/guide-to-monetary-banking-and-financial-terms/camel_rat_sys/

Hong Kong Monetary Authority [HKMA]. (2022, December 23). *Supervisory policy manual: Risk-based supervisory approach*. https://www.hkma.gov.hk/media/eng/doc/key-functions/banking-stability/supervisory-policy-manual/SA-1.pdf

Hutto, C. J., & Gilbert, E. E. (2014). Vader: A parsimonious rule-based model for sentiment analysis of social media text. *Proceedings of the International AAAI Conference on Web and Social Media*, *8*(1), 216–225. https://doi.org/10.1609/icwsm.v8i1.14550

Khatun, N. (2021). Applications of normality test in statistical analysis. *Open Journal of Statistics*, *11*(1). 113-122. https://doi.org/10.4236/ojs.2021.111006

Loughran, T., & McDonald, B. (2010). When is a liability not a liability? textual analysis, dictionaries, and 10-KS. *The Journal of Finance*, *66*(1), 35–65. https://doi.org/10.1111/j.1540-6261.2010.01625.x

Moody's Analytics. (2023). *BankFocus*. https://www.moodysanalytics.com/product-list/bankfocus

News API. (2023). *News API – search news and blog articles on the web. News API - Search News and Blog Articles on the Web*. https://newsapi.org/

O’Keefe, J. P. (2022, January 24). *The use of machine learning for bank financial stress tests: Prepared for the 3rd annual Marcus Evans conference - best practices for stress testing in financial institutions, New York USA*. http://dx.doi.org/10.2139/ssrn.4019533

Ong, L. L., Jeasakul, P., & Kwoh, S. (2013, August). *HEAT! A bank health assessment tool*. https://www.imf.org/external/pubs/ft/wp/2013/wp13177.pdf

Park, J., Shin, M., & Heo, W. (2021). Estimating the BIS capital adequacy ratio for Korean banks using machine learning: Predicting by variable selection using random forest algorithms. *Risks*, *9*(2). 32. https://doi.org/10.3390/risks9020032

Petropoulos, A., Siakoulis, V., Vlachogiannakis, N., & Stavroulakis, E. (2019, March). *Deep-Stress: A deep learning approach for dynamic balance sheet stress testing*. https://www.eba.europa.eu/sites/default/documents/files/document_library/Calendar/Conference-Workshop/2019/8th%20annual%20workshop%20documents/2%20DeepStress-A%20deep%20learning%20approach%20for%20dynamic%20balance%20sheet%20stress%20testing.pdf

Staudemeyer, R. C., & Morris, E. R. (2019). *Understanding LSTM -- a tutorial into Long Short-Term Memory Recurrent Neural Networks*. arXiv. https://arxiv.org/abs/1909.09586

Wong, S. L., & Wei, M. (2023, June). *The bank vulnerability index: A health check on ASEAN+3 banks and banking sectors*. https://amro-asia.org/wp-content/uploads/2023/08/AMRO-Working-Paper-23-02_The-Bank-Vulnerability-Index_-Aug-2023.pdf