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# Liquidity prediction on Vietnamese stock market using deep learning

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**Abstract**

Machine-learning methods have recently been successfully used in different areas, but there are also many fields where such studies have not been carried out. One of them is advanced issue regarding liquidity prediction and forecasting of financial time series. It is a very challenging task because this sphere is highly volatile and dynamic, especially if we consider emerging stock markets like the Vietnamese one. The authors proposed deep learning as the most modern technique to forecast the future directions of an emerging stock market and developed a predictive model to forecast liquidity for such a market. A fully-connected neural network based on Multilayer Perceptron (MLP), Mixed Deep Learning (MDL), and Linear Regression (LR) was tested. The following metrics were used: mean absolute error (MAE) and mean square error (MSE), and the best values of MSE in the MDL model were achieved. Based on the proposed model, which is the main contribution of the paper, better investment decisions can be achieved. The authors' solution is dedicated to and empirically verified on the Vietnamese stock market, so future works should extend the model to other ones, emerging and developed alike.

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*Keywords:* deep learning, stock market, liquidity prediction

## 1. Introduction

There are not many studies carried out on predicting liquidity by applying the technique of deep learning. Liquidity is a determinant of investment decisions on stock exchanges, affecting stock returns on investment through the cost trading to transfer the ownership of stocks.

Therefore, the implementation of the studies on liquidity is a significant contribution to improve investors' decisions [28]. The stock market is always characterised by uncertainty, and the existence of uncertainty in emerging markets, in particular. This study chooses the Ho Chi Minh Stock Exchange (HOSE) in Vietnam, an emerging market in Asia, to conduct liquidity forecasting.

The paper aims to develop a predictive model to forecast liquidity for an emerging market.

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The paper includes four sections. The second section presents related works, and the third covers the research methodology and the deep learning model for liquidity prediction on the Vietnamese stock market as well as experimental results. In the next section, we compare the model developed by us to other approaches. In the last section of the paper, the main conclusions and the future work are discussed.

## 2. Related Works

The application of deep learning is diversified in various fields in prediction and classification purposes. Plenty of studies on deep learning have stressed the financial areas such as bankruptcy prediction, credit evaluation, and stock price prediction. Several studies have been carried out to develop models to predict business failure. They are a source of information for different stakeholders such as authorities and management of banking sectors, shareholders, investors, state authorities, and many others. Odom and Sharda (1990)[17], are the pioneer authors who used neural networks in predictive models. Naidu and Govinda (2018)[16] proposed a prediction model by implementing a learning algorithm based on artificial neural networks and the random forest. They (2018)[16] analysed the bankruptcy situation faced by Polish companies during the period from 2000 to 2012. Alexandropoulos et al. (2019)[2] examined the predictive model for 150 companies in Greece. To forecast bankruptcy, these authors used Deep Dense Multilayer Perceptron, which provides better performance than other examined algorithms, i.e. Logistic Regression, the simple Multi-layer Perceptron, and the Naıve Bayes approach. Another common application of deep learning in previous studies is stock price prediction. Guresen et al. (2011)[6] achieved stock index prediction for NASDAQ Index by applying techniques such as multi-layer perceptron, dynamic artificial neural network, and hybrid artificial neural network. In the study of Moghaddam et al. (2015)[15], the authors constructed models to predict NASDAQ Index through the scaled conjugate gradient (SCG), using the Levenberg-Marquardt approach, one step secant method, and gradient descent with momentum. In a study by Balaji et al. (2018)[31], tthe authors used four different models such as Long-Short Term Memory, Gated Recurring Unit, Convolutional Neural Networks, and Extreme Learning Machines. The price prediction was applied for stock datasets in the SP BSE-BANKEX index from 12.07.2005 to 03.11.2017. Wang et al. (2016)[20] examined the predictive models applying an Elman recurrent neural network to the indices of Shanghai Stock Exchange, Taiwan Stock Exchange Capitalization Weighted Stock, Korean Stock Exchange, and Nikkei 225. Then the authors compared the proposed models with other techniques such as Back Propagation Neural Network, Multilayer Perceptron, and Stochastic Time effective Neural Network.

Based on the reviewed studies, deep learning demonstrates plausible benefits for financial market recognition and prognostics. However, there are a number of limitations that hinder its widespread adoption and require further development. Moreover, there are many areas where such studies have not been carried out. One of them is difficult issues regarding liquidity prediction and the forecasting of financial time series.// Therefore, in the next part of the paper, attention is paid to liquidity prediction for emerging stock markets by applying the technique of deep learning. The considerations are especially focused on overcoming different challenges and possible future opportunities.

## 3. Model development

### 3.1. Methodology

The main objective of this work is to improve liquidity prediction on the Vietnamese stock market using a deep learning model. The exploration was performed in the shape of the following activities:

A. Preparing data
B. Building deep learning model
C. Conducting an experimental analysis and comparing the results with other approaches which are near to the liquidity prediction

At the first stage, data was prepared for further analysis. The data was preliminarily analysed and statistically significant relationships were found that enable illiquidity prediction. Feature selection was performed based on correlations analysis. After preparing and selecting data, a deep learning model was developed. The tasks included the following:

- selection of the structure of a neural network (based on literature analysis and experience of the authors),
- determination of the number of hidden layers,
- choosing of activation functions,
- definition of output.

The last stage is related to performing experiments. The fully-connected neural network based on Multilayer Perceptron (MLP), Mixed Deep Learning (MDL), and Linear Regression (LR) was tested. The following metrics were used: mean absolute error (MAE) and mean square error (MSE). The results were compared to other approaches presented in selected related works.

### 3.2. Data description and preparation

The sample period ranges from 4 Jan 2011 to 28 Dec 2018. A sample of daily data of 220 companies representing different sectors listed on the Ho Chi Minh City Stock Exchange was employed by the authors. Variables to describe market liquidity in the study are as follows (Sarr and Lybek (2002)[18], Marshall et al.(2013)[13], Amihud (2002)[3]):
1) trading volume ($VOL$), capture the number of traded shares;
2) trading value ($VAL$), the amount of traded value during a specified period
3) turnover ratio ($TO$) a ratio, measured as the number of traded shares for stock i on each day over the number of shares outstanding.
4) Bid-Ask spread ($SPRD_{i,d}$) the difference between the best ask price ($PA_{i,d}$) and the best bid price ($PB_{i,d}$).
5) The relative spread ($RESPR_{i,d}$), calculated for stock i on day d as $RESPR_{i,d} = (PA_{i,d} - PB_{i,d})/[(PA_{i,d} + PB_{i,d})/2]$.
6) AMH measure, an illiquidity measure for the resilience dimensions as $AMH_{i,d} = |R_{i,d}|/VAL_{i,d}$, where $R_{i,d}, VAL_{i,d}$ are the return, and the trading value for stock i on day $d$. $VOL, VAL, and TO$ are liquid proxies, the higher proxies are, the better liquidity is. $SPRD_{i,d}$ and $RESPR_{i,d}$ have negative relation with the stock liquidity. $AMH$ has negative relation with liquidity. From definition the relationship between bid-ask spread and relative spread is strong, between trading volume and trading value too. The coefficient of correlations is high, 0.96 and 0.99 respectively (see table 1) for sampled company (BENTRE AQUAPRODUCT IMPORT AND EXPORT Joint Stock Comp.).

Table 1. Coefficients of correlation for all variables

| | **SPRD** | **RESPR** | **TO** | **Vol** | **VAL** | **AMH** |
|---|---|---|---|---|---|---|
| SPRD | 1.0000 | | | | | |
| RESPR | 0.9563 | 1.0000 | | | | |
| ¿TO | -0.0447 | -0.0364 | 1.0000 | | | |
| Vol | -0.1116 | -0.1025 | 0.3146 | 1.0000 | | |
| Val | -0.1034 | -0.1034 | 0.3100 | 0.9901 | 1.0000 | |
| AMH | 0.2024 | 0.1781 | -0.0391 | -0.0888 | -0.0943 | 1.0000 |

We also check correlation between delayed variables (1 until 7 days). The correlation coefficients are very weak (see table 2-5). To calculate the coefficients of correlation we used relative change (in %),

Table 2. Coefficients of correlation for bid-ask SPRD

| | SPRD | SPRD1 | SPRD2 | SPRD3 | SPRD4 | SPRD5 | SPRD6 | SPRD7 |
|---|---|---|---|---|---|---|---|---|
| SPRD | 1.0000 | | | | | | | |
| SPRD1 | -0.1207 | 1.0000 | | | | | | |
| SPRD2 | 0.0084 | -0.1207 | 1.0000 | | | | | |
| SPRD3 | 0.0537 | 0.0084 | -0.1207 | 1.0000 | | | | |
| SPRD4 | -0.0361 | 0.0537 | 0.0084 | -0.1207 | 1.0000 | | | |
| SPRD5 | 0.0066 | -0.0360 | 0.0537 | 0.0084 | -0.1208 | 1.0000 | | |
| SPRD6 | 0.0256 | 0.0067 | -0.0360 | 0.0536 | 0.0084 | -0.1209 | 1.0000 | |
| SPRD7 | 0.0084 | 0.0255 | 0.0067 | -0.0360 | 0.0537 | 0.0084 | -0.1208 | 1.0000 |

where 1,. . . ,7 means the number of delays in days

Table 3. Coefficients of correlation for bid-ask RESPR

| | RESPR | RESPR1 | RESPR2 | RESPR3 | RESPR4 | RESPR5 | RESPR6 | RESPR7 |
|---|---|---|---|---|---|---|---|---|
| RESPR | 1.0000 | | | | | | | |
| RESPR1 | -0.1222 | 1.0000 | | | | | | |
| RESPR2 | 0.0101 | -0.1222 | 1.0000 | | | | | |
| RESPR3 | 0.0534 | 0.0102 | -0.1222 | 1.0000 | | | | |
| RESPR4 | -0.0366 | 0.0534 | 0.0102 | -0.1222 | 1.0000 | | | |
| RESPR5 | 0.0073 | -0.0366 | 0.0534 | 0.0101 | -0.1223 | 1.0000 | | |
| RESPR6 | 0.0256 | 0.0074 | -0.0365 | 0.0533 | 0.0101 | -0.1224 | 1.0000 | |
| RESPR7 | 0.0168 | 0.0256 | 0.0074 | -0.0365 | 0.0534 | 0.0101 | -0.1223 | 1.0000 |

where 1,. . . ,7 means the number of delays in days

Table 4. Coefficients of correlation for Vol

| | Vol | Vol1 | Vol2 | Vol3 | Vol | Vol5 | Vol6 | Vol7 |
|---|---|---|---|---|---|---|---|---|
| Vol | 1.0000 | | | | | | | |
| Vol1 | -0.0239 | 1.0000 | | | | | | |
| Vol2 | -0.0005 | -0.0239 | 1.0000 | | | | | |
| Vol3 | 0.0183 | -0.0005 | -0.0239 | 1.0000 | | | | |
| Vol4 | -0.0062 | 0.0182 | -0.0005 | -0.0240 | 1.0000 | | | |
| Vol5 | 0.0234 | -0.0062 | 0.0182 | -0.0005 | -0.0240 | 1.0000 | | |
| Vol6 | -0.0102 | 0.0234 | -0.0062 | 0.0182 | -0.0005 | -0.0240 | 1.0000 | |
| Vol7 | -0.0003 | -0.0102 | 0.0234 | -0.0062 | 0.0182 | -0.0005 | -0.0240 | 1.0000 |

where 1,. . . ,7 means the number of delays in days

Table 5. Coefficients of correlation for Val

| | Val | Val1 | Val2 | Val3 | Val | Val5 | Val6 | Val7 |
|---|---|---|---|---|---|---|---|---|
| Val | 1.0000 | | | | | | | |
| Val1 | -0.0343 | 1.0000 | | | | | | |
| Val2 | -0.0043 | -0.0343 | 1.0000 | | | | | |
| Val3 | 0.0657 | -0.0043 | -0.0343 | 1.0000 | | | | |
| Val4 | -0.0014 | 0.0657 | -0.0043 | -0.0344 | 1.0000 | | | |
| Val5 | 0.0016 | -0.0014 | 0.0657 | -0.0043 | -0.0344 | 1.0000 | | |
| Val6 | 0.0167 | 0.0016 | -0.0014 | 0.0657 | -0.0043 | -0.0344 | 1.0000 | |
| Val7 | 0.0020 | 0.0167 | 0.0016 | -0.0015 | 0.0657 | -0.0043 | -0.0344 | 1.0000 |

where 1,. . . ,7 means the number of delays in days

### *3.3. Deep learning model*

The developed deep neural network is a regression model. While developing the networks, we based on related works and our experience. The optimal structure of networks was determined based on experimental results. We performed several dozen experiments with different hyper-parameters and parameters of networks (e.g. type of layers, number of layers, number of neurons, activation function, batch size, and number of epochs). First, a fully-connected neural network based on multilayer perceptron (MLP) was developed. The parameters of MLP are as follows:

- Input layer: 60 neurons (reLU activation),
- two hidden layers: from 30 and 20 neurons (reLU activation),
- Output layer: 1 neuron (reLU activation).

The second stage of model development process is mixed deep learning (MDL), which consists of the following layers:

- Input layer: 60 neurons (reLU activation),
- Recurrent layer: 300 neurons (reLU activation)),
- Three fully-connected hidden layers with dropuots: from 300 to 20 neurons (reLU activation)),
- Output layer: 1 neuron (reLU activation).

The output neuron assumes values in the range from 0 to 1. The result is interpreted as the normalized value of given liquidity measure.

Input vector is defined as follows:

$$X = \{X^{VOL}, X^{TO}, X^{RESPR}, X^{AMH}\} \tag{1}$$

Where:
$X^{VOL} = \{x^{VOL}_{t-1}, x^{VOL}_{t-2,} \ldots, x^{VOL}_{t-n}\}$ - historical values of *VOL* variable ($t$ - time of prediction, $n$ - number of historical values),
$X^{TO} = \{x^{TO}_{t-1}, x^{TO}_{t-2,} \ldots, x^{TO}_{t-n}\}$ - historical values of *TO* variable,
$X^{RESPR} = \{x^{RESPR}_{t-1}, x^{RESPR}_{t-2,} \ldots, x^{RESPR}_{t-n}\}$ - historical values of *RESPR* variable,
$X^{AMH} = \{x^{AMH}_{t-1}, x^{AMH}_{t-2,} \ldots, x^{AMH}_{t-n}\}$ - historical values of *AMH* variable,

The deep neural network has a mixed architecture. The output is defined as follows:

$$y = f(y^1, y^2, \ldots, y^L) \tag{2}$$

Where:
$y^l$ denotes a layer in which $l = 1, 2, \ldots L$ ($L$ denotes a number of layers),
$f()$ denotes the output activation function.

Let *dense* denotes the layer composed of certain number of neurons (*RNN* denotes a recurrent layer), *neurons* denotes a number of neurons, *relu* denotes rectified linear unit activation function defined as follows [**?** ]:

$$relu(z) = \begin{cases} z, if\ z \geq 0 \\ 0, otherwise \end{cases} \tag{3}$$

The first (input) layer is defined as follows:

$$y = dense([X^{VOL}, X^{TO}, X^{RESPR}, X^{AMH}], neurons, relu) \tag{4}$$

The second layer is the RNN layer defined as follows:

$$y^2 = RNN(y^1, neurons, relu). \tag{5}$$

Next layers are fully-connected layers and dropout layers. The visualization of the developed model is presented in Fig. 1.

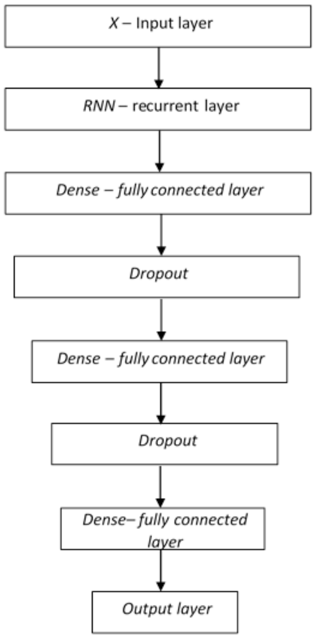


Fig. 1. Visualization of the model.

### 3.4. Experimental results

The aim of the experiments was the evaluation of developed liquidity prediction model. We randomly selected 25% of companies for experiments. The dataset consists of 31873 rows and and input vector consists of 56 attributes (14 historical values of *VOL*,*TO*,*RESPR* and *RESPR* variables). The predicted variable was *RESPR* (normalized values - period 0..1). This sub-section presents the results achieved by the developed method (as it was mentioned earlier, during the development phase, several dozen experiments were performed in order to set the hyperparameters and parameters of neural networks). We used mean absolute error (MAE) and mean square error (MSE) as metrics. The experiments related to:

- Mixed Deep Learning (MDL),
- Multilayer Perceptron (MPL),
- Linear Regression (LR).

Hyperparameters and parameters in all models were determined on the basis of related works and experimentally. The results are presented in table 6).

Table 6. Evaluation results

| Method | MAE | MSE |
|---|---|---|
| MDL | 0.01964521 | 0.00078546 |
| MLP | 0.05553737 | 0.00293308 |
| LR | 0.05446701 | 0.01986106 |

The lowest MSE and lowest MAE has been achieved by Mixed Deep Learning model. The LR model achieved higher values of MAE and MSE than MDL. At the same time the LR model achieved lower value of MAE than MLP model, but higher value of MSE than MLP model. The best values of MSE in MDL model has been achieved in $10^{th}$ epoch. (fig. 2).

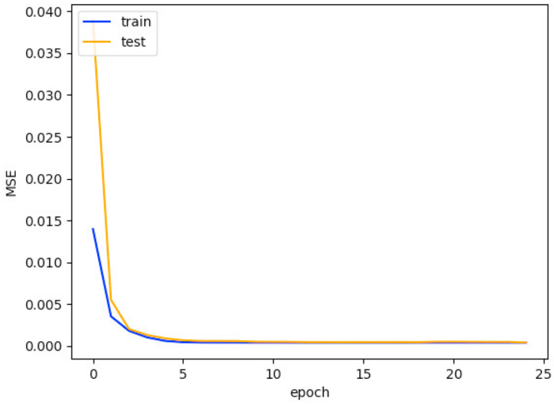


Fig. 2. MSE values of MDL model

## 4. Discussion

In this section, we tried to compare the developed MDL model to other approaches. Table 7 presents the results of the comparison of the developed model to other methods presented in the literature of subject, which aim is close to liquidity prediction.

Table 7. Comparison of the different models

| No | Authors | Year | Model(s) | MSE |
|---|---|---|---|---|
| 1. | A. Jayanth Balaji et al.[31] | 2018 | Convolutional Neural Network<br>Gated Recurrent Unit<br>Long Short-Term Memory<br>Extreme Learning Machines | 0.1303<br>0.0820<br>0.1011<br>0.1255 |
| 2. | P.M. Addo et al.[2] | 2018 | Logistic regression<br>Random forest<br>Boosting approach<br>Deep learning | 0.247955<br>0.097403<br>0.041999<br>0.120964 |
| 3. | S. Liu et al.[3] | 2018 | Multi Layer Perceptron | 0.000553 |
| 4. | MDL - this research | 2020 | Mixed Deep Learning | 0.00078546 |

The methods are characterised by a high diversity of MSE. It results from three main factors: the type of method, the number and characteristics of attributes, and the number of data rows. The highest value of MSE (0.247955) was achieved by logistic regression - pos. 2, the lowest value of MSE (0.000553) was achieved by multi-layer perceptron - pos. 3. The MSE of most of the approaches is lower than 0.14. The method developed in this paper (MDL) achieved a higher MSE than the approach presented in [8], however the results presented in [8] are based on simulated data in a high degree. a high degree. Therefore, the MSE can depend on the simulation method. The results achieved by MDL are based on real data. Generally speaking, it is also difficult to develop a general/universal model for liquidity prediction which can be used in the stock market in different countries. For example, the liquidity characteristics in the case of emerging markets and developed markets may differ.

## 5. Conclusions

In this paper, we presented a deep learning model for liquidity prediction on Vietnamese stock market. The main findings are related to developing the structure of model and it's empirical verification. Liquidity (the ease of trading securities) is one of the key elements which allowes the investor to decide whether to invest or not. The liquidity attracts investors on the market, requirening fast order processing and the ability to convert securities into cash at the lowest cost. Selling illiquid shares quickly can be difficult or even impossible without accepting lower prices. Liquidity is related to a liquidity premium defined "as the extra return that the illiquid stock must earn so that the investor attains the same level of utility as in the case of a perfectly liquid stock [30]. Therfore, the liquidity prediction is very important, based on liquidity forecast the investment decisions can be taken. Our study contributes to the empirical evidence on liquidity of the Vietnamese stock market, and indicates the listed companies might have benefits by enhancing the liquidity. It leads to a lower on cost of capital through its influence on expected return of investors. The aim of this paper was to develop a predictive model to forecast liquidity of selected market. Authors considered three models: Linear Regression, Mixed Deep Learning, and Multilayer Perceptron. It seems, that Linear Regression model is the worst tool to predict liquidity on HOSE (it achieved the highest value of Mean Square Error and comparable - a little lower - value of Mean Average Error). The study indicates that Mixed deep learning is the best technique for liquidity prediction on HOSE. The main disadvantage of presented approach is the utilization only on Vietnamese stock market. Therefore, the future works should be related to verification the model on other stock markets (both emerging and developed). Also different types of neural layers (e.g. CNN, LSTM) should be tested.

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