Bangladesh Share Market Forecasting Using Hidden Markov Model

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***Abstract*—Stock markets are among the most complicated systems, making it difficult to model them using dynamical equations. The main reason is that stock prices are affected by a range of unknown factors such economic conditions, business policy changes, investor supply and demand, and so on. Stock markets are particularly volatile because these elements are continually shifting. In Machine Learning, stock price forecasting is a typical non-stationary pattern identification task. A lot of research has gone into applying [1] Artificial Intelligence and Machine Learning techniques like the Hidden Markov Model to forecast stock behavior based on past performance. The HMM model was used to [2] forecast stock prices. The daily opening, closing, high, and low indices were used as continuous observations from the underlying hidden in our model. It may be able to forecast the future price of a stock. It will benefit people, and as a result, they will be interested in investing in the stock market.**

***Index Terms*—HMM, AIC, BIC and MAPE**

I. Introduction

The stock or share market is a system in which entrepreneurs who require capital for their businesses can obtain it at a low cost from small institutions. People have benefited from investing in the stock market. The Bangladesh stock market had a great year for investors.Bangladesh's stock market plummeted at the start of 2011. As a result, we can say that it is one of the most complex systems, with price forecasting being quite unpredictable. There are a number of unknown variables that influence stock prices, such as economic conditions, company policy changes, supply and demand among investors, and so on. These variables are constantly changing, resulting in extremely volatile or unpredictable financial markets. Stock price prediction is a non-stationary pattern recognition problem in Machine Learning. We have been developed a system that forecast the future price of a stock, and people benefits as well as be interested in investing their money in the stock market as a result. We used [3] Hidden Markov Models (HMM) to analyze stock markets because they have a strong probabilistic framework for recognizing patterns in stochastic processes. HMM can be more effective for volatile stocks.

II. Literature Review

In this section, we'll go over some existing share market forecasting techniques proposed by other authors. To achieve better results, various share market forecasting techniques have been implemented by various authors. Kamley et al. [4] proposed a paper titled Share market performance forecasting using machine learning techniques: A review. This paper provides an overview of the machine learning techniques that were previously used to forecast share performance. The authors stressed the significance of prediction algorithms in identifying the most important variables in a stock market dataset. The authors were able to successfully analyze shared performance. Nayak et al. [5] proposed stock market prediction models for India. The authors created two distinct models for daily and monthly prediction using supervised machine learning algorithms. For daily prediction models, historical prices are combined with sentiments. Using a monthly prediction model, the authors investigated whether there is any similarity between the trends of two months. Y. Ishii and K. Takeyasu [6] proposed a hybrid method to improve forecasting accuracy utilizing genetic algorithms and its application to stock market price data. The authors determined ARMA model parameters to continue the estimation of smoothing constants. The following [7] method is quite useful for time series which contain different trend characteristics. Moedjahedy et al. [8] proposed a paper titled stock price forecasting on telecommunication sector companies listed on the Indonesia stock exchange using machine learning algorithms. In this paper, the authors used Gaussian processes and SMOreg algorithms. Machine learning methods are extremely useful for forecasting stock prices. The authors used five different companies in the telecommunications sector to predict stock price in this paper. The SMOreg algorithm outperforms the Gaussian process, according to the paper that follows.

III. Proposed Model

A. Hidden Markov Models (HMM)

Hidden Markov Models have a high success rate in pattern recognition. It has been used to examine patterns in speech, handwriting, gestures, and a wide range of DNA sequences. The transition from one state to the next is a Markov Process in which the next state is determined by the current state. HMM is a model of observations that depend on system states that are 'hidden' to the observer, hence the name Hidden Markov Models. The states in HMM are always discrete, continuous.

B. Financial Time Series analysis

Markov chain with a hidden variable Markov Models have been shown to be an efficient method for studying non-stationary processes. The stock market is a non-stationary system with ever-changing results. Suppose, Observation Sequence 0_t be a vector of four elements- daily close, open, high and low States and S_t o be one of the assumed states on day t. Observations 0_t are independent and modelled as Multivariate Gaussian distributed takes real values. HMM is a finite state machine so S_t can take only discrete values. We will be using the some notations to define Hidden Markov Models.
Number of observations, T
Latency, K
Number of States, $N(S_t = S_1, S_2 \ldots , S_N)$
Observation Sequence, 0_t
Initial State Probability, P_0

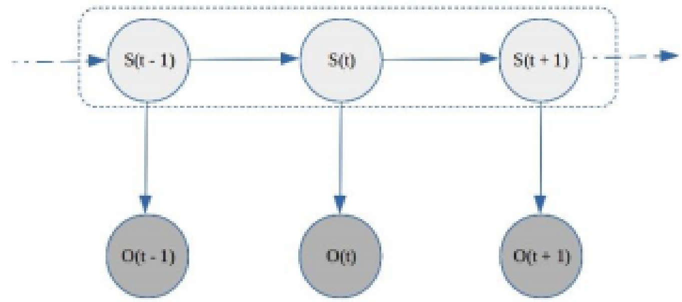

Fig. 1. Hidden Markov Process

State Transition Matrix, A = $[a_i j]$ where $a_i j$ the state transition probability from i to j
Observation Probabilities,greek $_i$ $\sum_i$ i= 1,2, . . N where greek $_i$, $\sum_i$ are the mean and covariance matrix for Gaussian distribution for state i The Hidden Markov Model can be represented as = (A, greek , $\sum$,P_0)

C. Prediction of Stock Prices

To compute the log-likelihood of K for predicting the stock price the next day. By shifting the window by one day in the direction of past data 1, we can compare it to the log-likelihood of all previous sub-sequences of the same size. Then we found a day in the past whose log-likelihood of its K previous observations is closest to the sub-sequence whose price is to be predicted the next day.

j = $argmin_i$(— P (O_t, $O_t - 1$, $O_t - 2$,.., $O_t - K$) —) - P ($O_t - i$, $O_t - i - 1$, $O_t - i - 2$,.., $O_t - K$) — —) where i is 1,2,..,T/K

The price difference between the indicated day and the next day is then computed. This adjustment is then multiplied by the current day's price to arrive at our forecast for the following day.

$O_t + 1$ = O_t + $O_t - j + 1$ - $O_t - j$

We have obtained the true observation, add it to our dataset, and fine-tune our model parameters to ensure that our model does not diverge. In other words, we have fixed the size of our sub-sequence and search previous data for a comparable sub-sequence. The detected sub-behavior sequence's is then mapped to the sub-sequence used for prediction.

We trained a set of models by varying the number of states (N) in the state space to find the model with the most states. We examined the number of states in G ranging from [2,25] to [2,25]. Taking more sates will increase accuracy but may result in overfitting. Negative values were assigned to each of the models, and the model with the lowest value was chosen. This tends to favor a complex model, implying that the number of states chosen may be greater and may result in overfitting. A penalty term is added to the negative log probability to avoid this problem. Depending on the penalty term, we applied varying degrees of constraint to the model. We investigated the [9]Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), which are two distinct performance measure metrics. In AIC, we add the number of model parameters to the negative loglikelihood value, whereas in BIC, add the product of the number of model parameters and the logarithm of the number of observation samples used.

AIC = - 2 log (P ($O_train|$)) - 2p

BIC = - 2 log (P ($O_train|$)) - p.log(T)

These are the results of the performance measurement model. When a false negative result is more misleading than a false positive, AIC is superior; when a false positive is equally or more misleading than a false negative, BIC is superior. In our project, we chose the number of states in our target model based on BIC as the model's performance measure.

IV. Implementation

Mean Absolute Percentage Error (MAPE) [10] has been used as performance metric which is define as

$$MAPE = \sum_{i=1}^{m} \frac{|Predicted(i) - True(i)|}{True(i)}$$

Our primary goal is to determine the effectiveness of HMM in predicting stock prices. The hmmlearn, an open source Python package has been used, to train the model and calculate the probability of the data. We obtained a dataset from investing.com of six companies: Unilever Consumer Care Limited (UNILEVERCL), Grameenphone Ltd (GP), Dutch-Bangla Bank Ltd (DUTCHBANGL), Beximco Pharmaceiticals Ltd. (BXPHARMA), Berger Paints Bangladesh Ltd. (BERGERPBL), and British American Tobacco Bangladesh Company Ltd (BATBC). We used four types of features: opening price, closing price, high and low for at least the previous 1599 working days, which equates to more than four years of daily stock prices. The last 90 observations were saved for testing, while the rest of the data was used to train the model. Working backwards, improve the model's ability to forecast the 89th, and so on. When we return the model after each iteration, the number of training samples will be increased by one if necessary. We used a latency of 50 and 10000 iterations.

We used the Forward algorithm to observe the data sequence. The Viterbi algorithm can be used to find the best hidden state sequence. The Baum-Welch algorithm is used to find the best model parameters. We computed the MAPE and displayed the predicted and actual prices to compare the findings. We used a vector with the lowest likelihood. To optimize our model, The model with the lowest BIC value is chosen.

Company Name Code	Start Date	End Date	No. of Days
UNILEVERCL	05-Jun-2014	16-May-2021	1613
GP	18-Nov-2009	16-May-2021	2707
DUTCHBANGL	26-Nov-2007	16-May-2021	3189
BXPHARMA	11-Aug-2014	16-May-2021	1598
BERGERPBL	26-Nov-2007	16-May-2021	3097
BATBC	03-Jul-2014	16-May-2021	1599

TABLE I
Data Summary

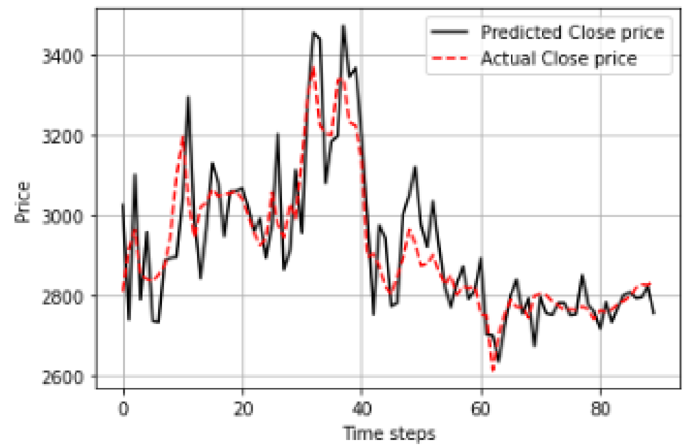

Fig. 2. Unilever Consumer Care Limited, Close, State = 21

V. Result Analysis

This section has been desinged for result part. All of the figures are the accurate evidences of our research shown below:

Code	Close	Open	High	Low
UNILEVERCL	0.0254658	0.0279011	0.0271942	0.0241991
GP	0.0138668	0.0179751	0.0137767	0.0136781
DUTCHBANGL	0.013355	0.0156578	0.012921	0.0105929
BXPHARMA	0.0416561	0.0401255	0.0297477	0.0401381
BERGERPBL	0.0254288	0.031876	0.0229392	0.0218087
BATBC	0.0270006	0.0340903	0.0297567	0.0250588

TABLE II
Data Summary

VI. Conclusion

The Hidden Markov Model is a data forecasting technique. We used it to forecast the value of Bangladesh's stock market. Except for Baximco, we discovered that the accuracy level is high after implementing the model. It is because of Bangladesh's current situation. A variety of factors influence the stock price in Bangladesh's stock market. It is known as a factor. As these circumstances change, the stock price rises and falls. We're doomed if we don't. If these factors are considered, the accuracy level may be higher.

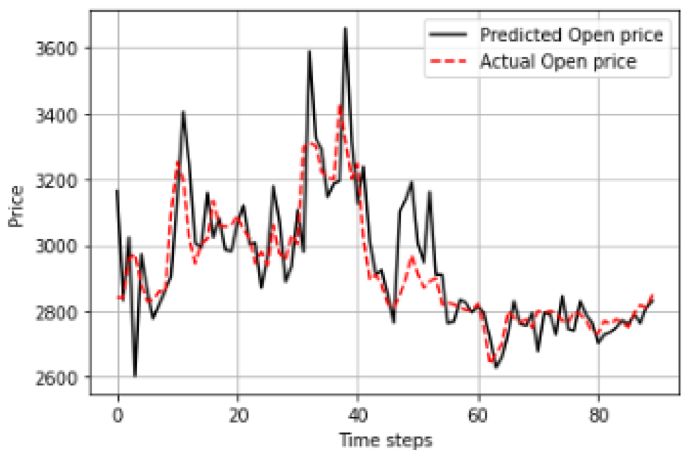

Fig. 3. Unilever Consumer Care Limited, Open, State = 21

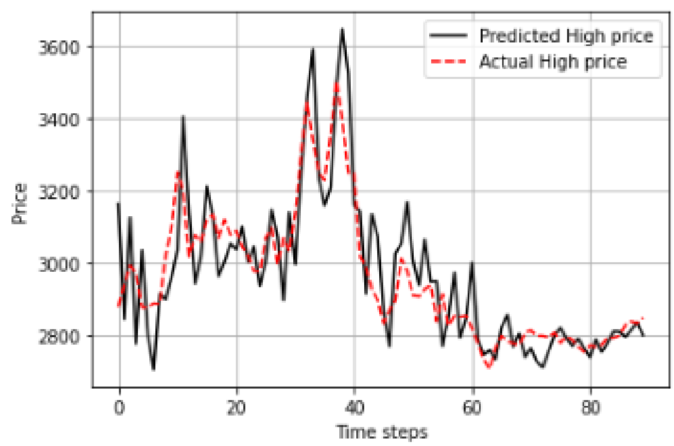

Fig. 4. Unilever Consumer Care Limited, High, State = 21

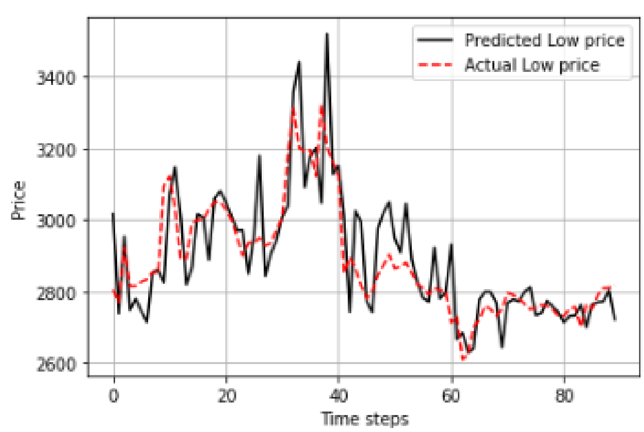

Fig. 5. Unilever Consumer Care Limited, Low, State = 21

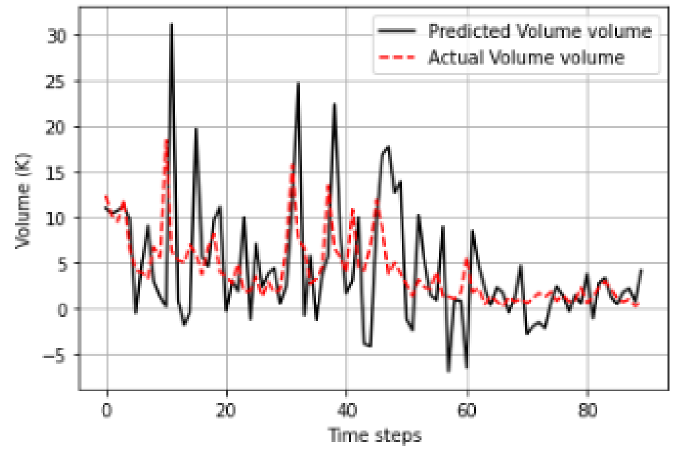

Fig. 6. Unilever Consumer Care Limited, Volume, State = 21

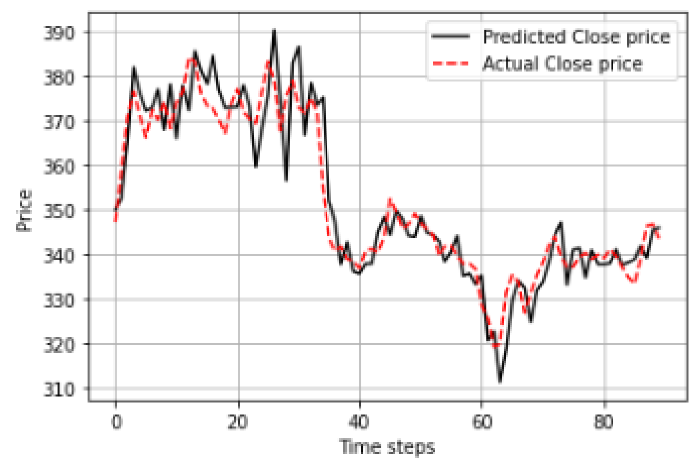

Fig. 7. Grameenphone Ltd. Close,State = 24

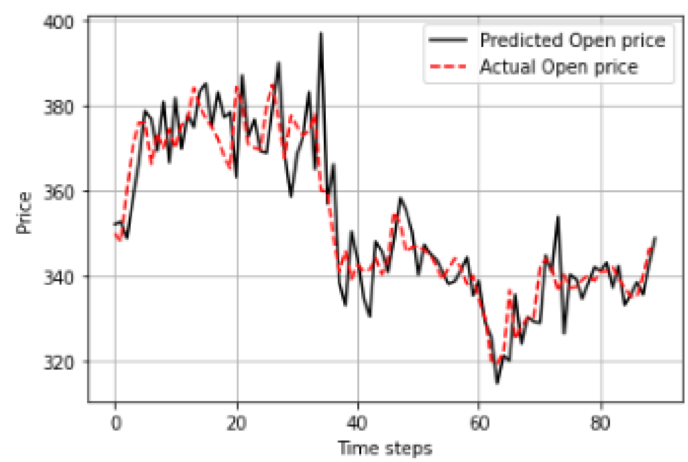

Fig. 8. Grameenphone Ltd., Open, State = 24

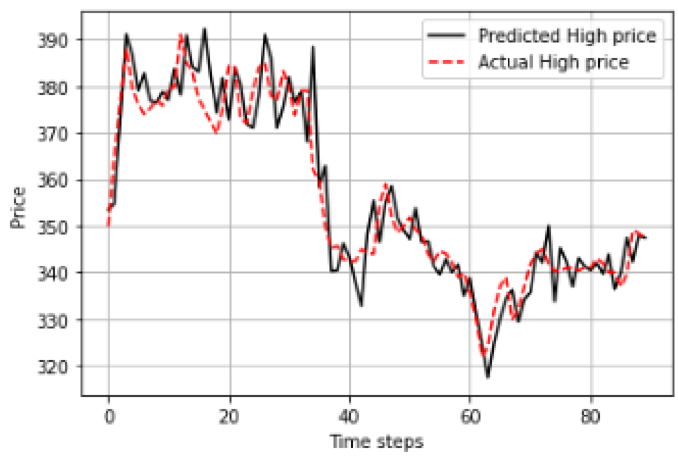

Fig. 9. Grameenphone Ltd., High, State = 24

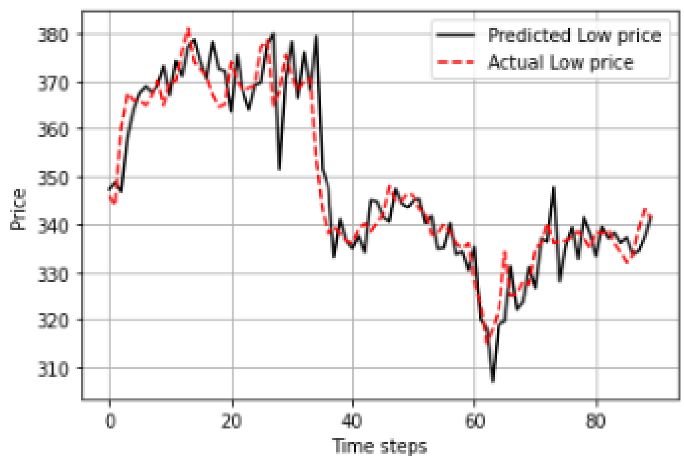

Fig. 10. Grameenphone Ltd., Low, State = 24

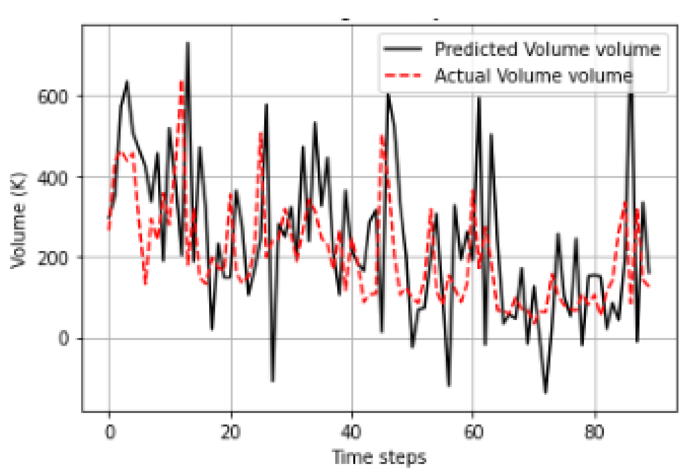

Fig. 11. Grameenphone Ltd., Volume, State = 24

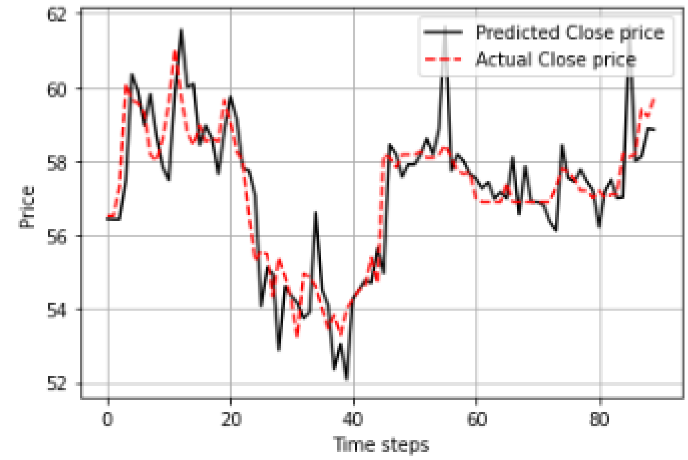

Fig. 12. Dutch-Bangla Bank Ltd., Close,State = 24

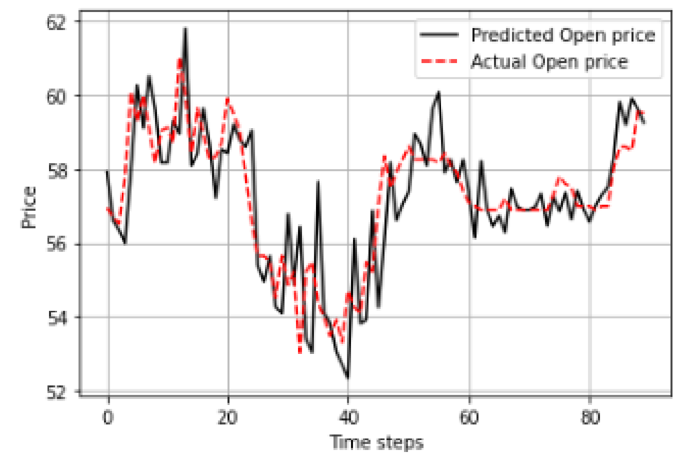

Fig. 13. Dutch-Bangla Bank Ltd., Open, State = 24

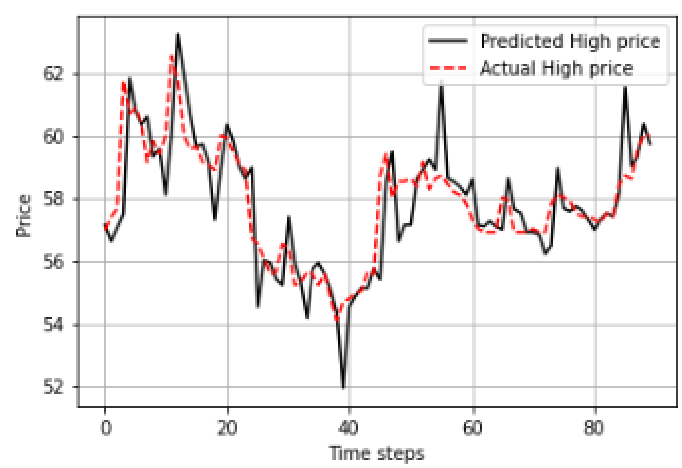

Fig. 14. Dutch-Bangla Bank Ltd., High, State = 24

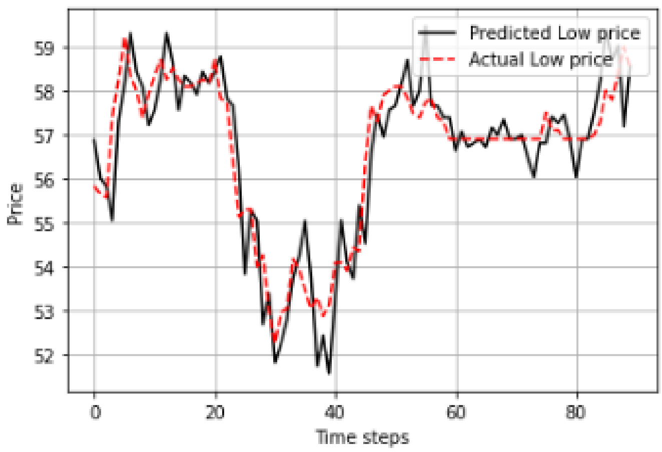

Fig. 15. Dutch-Bangla Bank Ltd., Low, State = 24

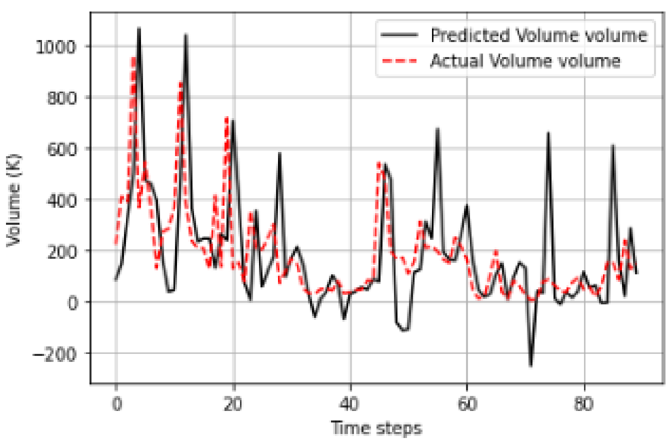

Fig. 16. Dutch-Bangla Bank Ltd, Volume, State = 24

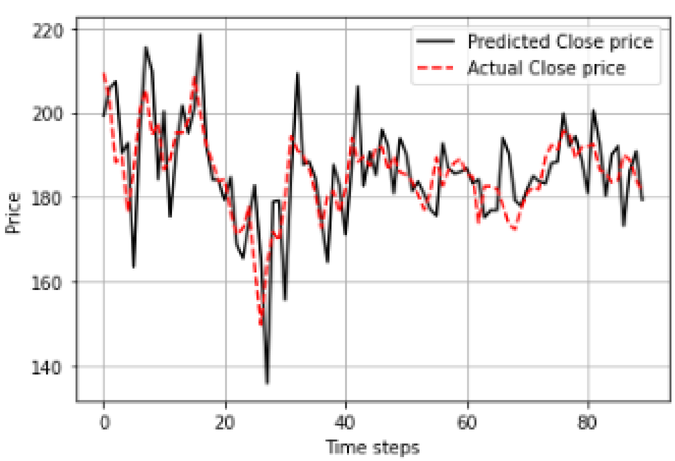

Fig. 17. Beximco Pharmaceiticals Ltd., Close,State = 20

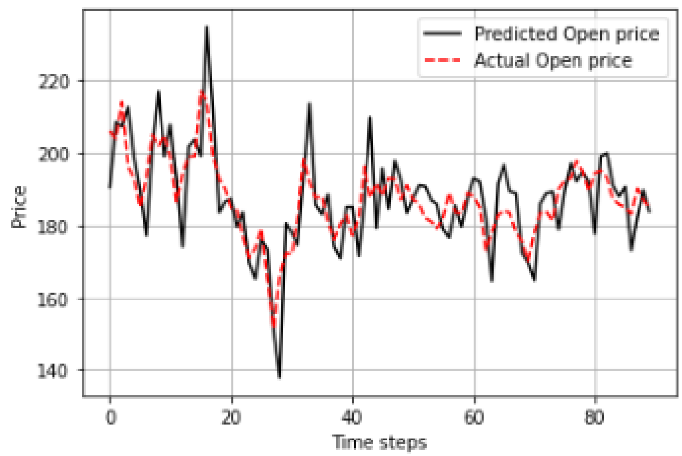

Fig. 18. Beximco Pharmaceiticals Ltd., Open, State = 20

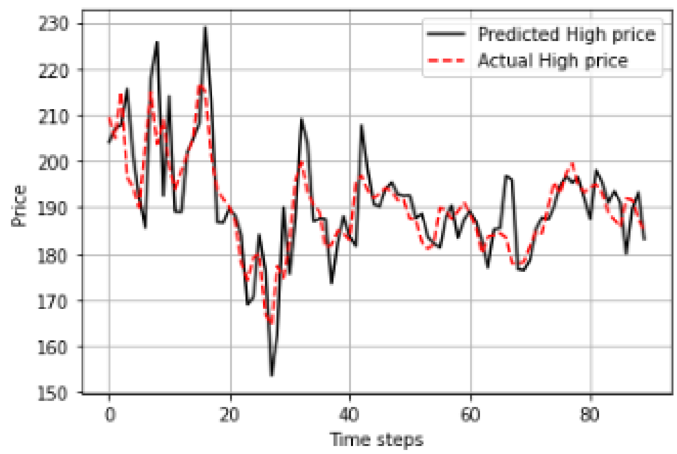

Fig. 19. Beximco Pharmaceiticals Ltd.., High, State = 20

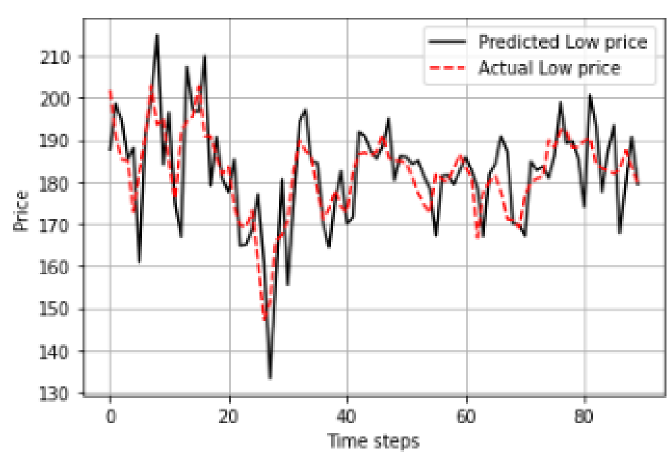

Fig. 20. Beximco Pharmaceiticals Ltd.., Low, State = 20

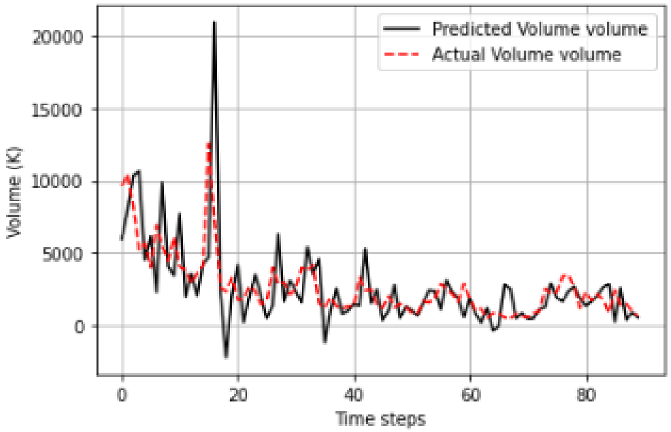

Fig. 21. Beximco Pharmaceiticals Ltd. Volume, State = 20

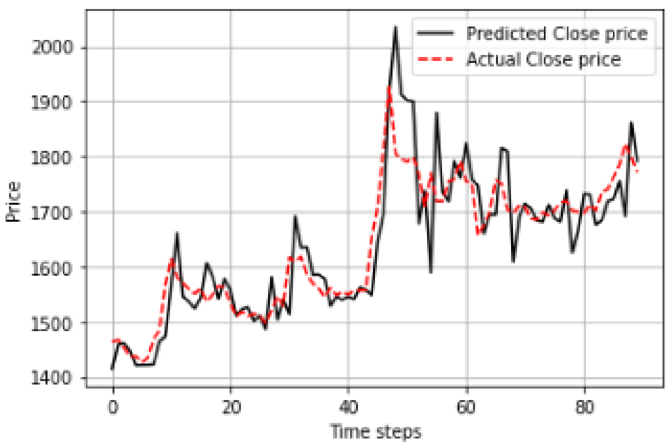

Fig. 22. Berger Paints Bangladesh Ltd., Close,State = 24

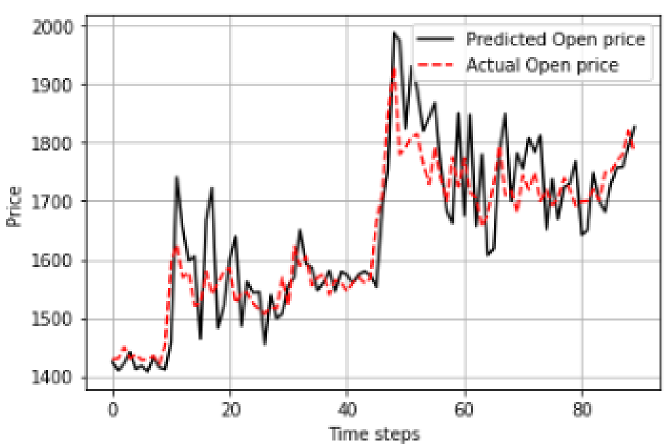

Fig. 23. Berger Paints Bangladesh Ltd, Open, State = 24

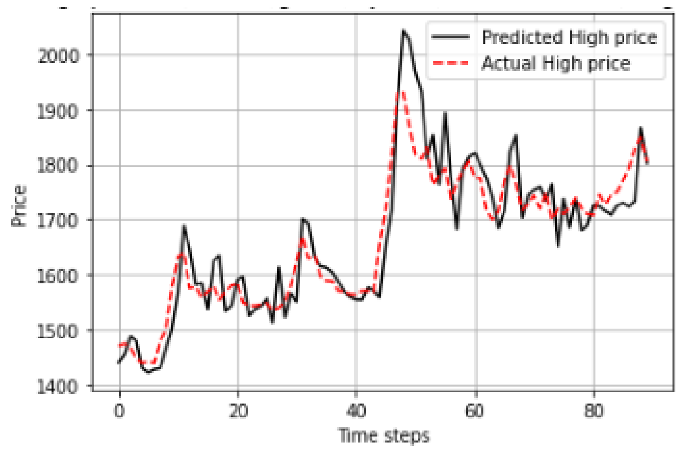

Fig. 24. Berger Paints Bangladesh Ltd, High, State = 24

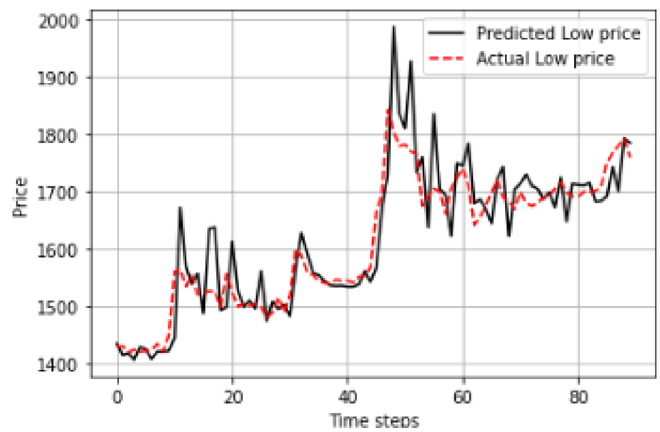

Fig. 25. Berger Paints Bangladesh Ltd., Low, State = 24

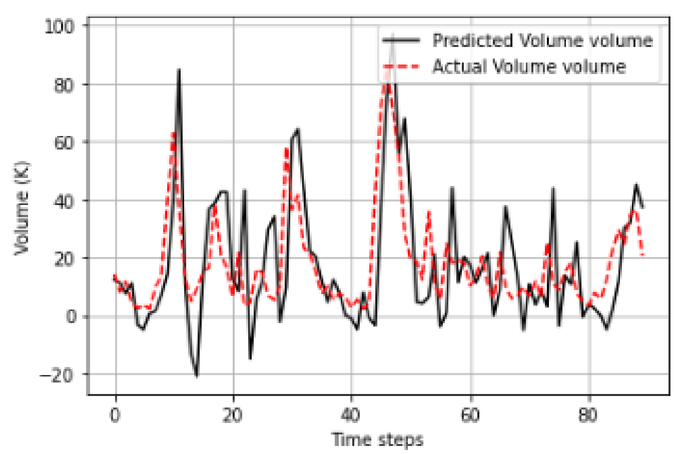

Fig. 26. Berger Paints Bangladesh Ltd. Volume, State = 24

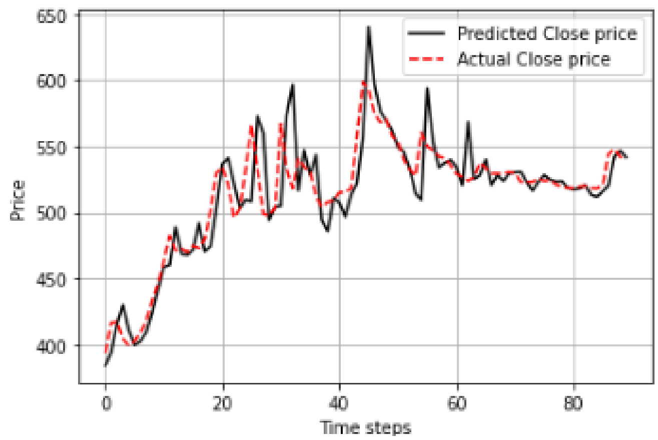

Fig. 27. BATBC, Close,State = 23

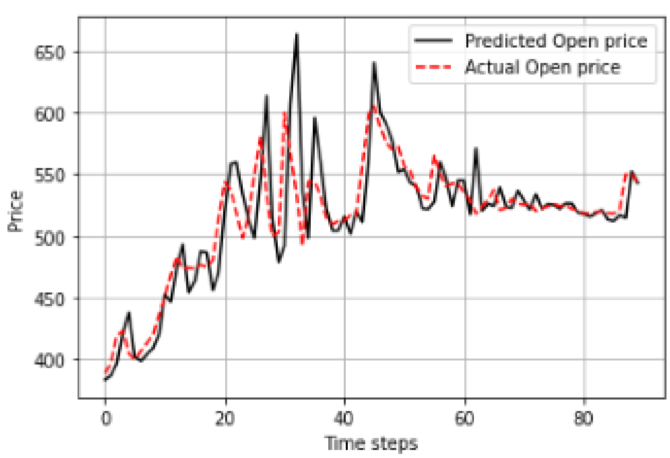

Fig. 28. BATBC, Open, State = 23

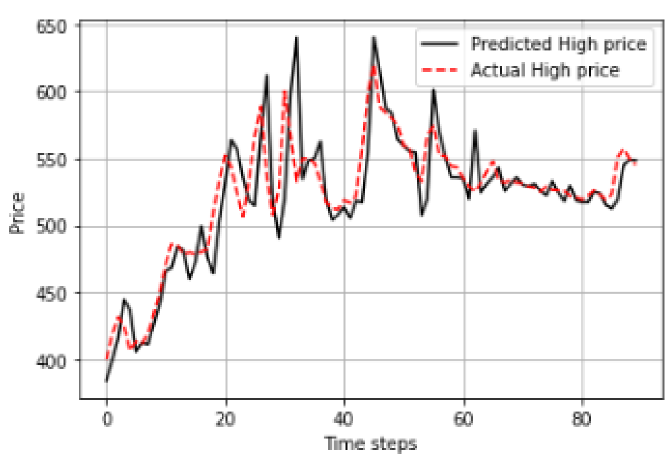

Fig. 29. BATBC, High, State = 23

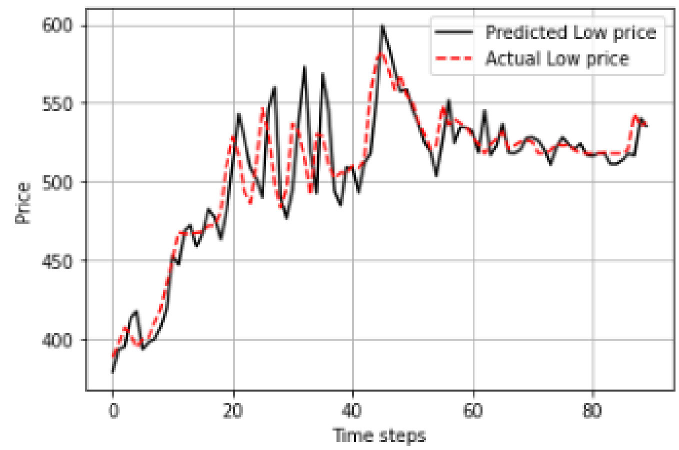

Fig. 30. BATBC, Low, State = 23

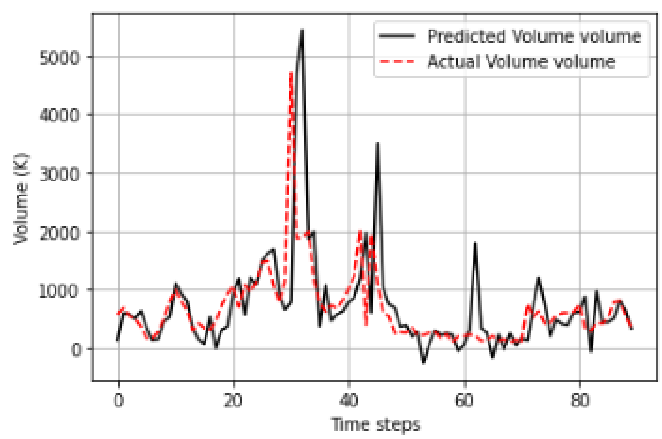

Fig. 31. BATBC Volume, State = 23

A. *Limitations & future work*

Our project has some constraints. We don't have much company for forecasting. Because we can take more states while dealing with over-fitting, our accuracy can be greater than the resulted value. However, it produces good results. HMM can be used in a variety of industries.

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