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11 authors, including:

August Thio-ac
Technological University of the Philippines

Daniel Cabrales
Technological University of the Philippines

Timothy Amado
Technological University of the Philippines

Romeo Jr Lumabiang Jorda
Technological University of the Philippines

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Stock Price Prediction and Portfolio Optimization Using Hidden Markov Model and Quadratic Programming

August C. Thio-ac[1], Daniel D. Cabrales[1], Drexanne E. Calibara[1], Maries V. Madrazo[1], Agustine Christian C. Matawaran[1], Genesis E. Micaller[1], Edmon O. Fernandez[1], Timothy M. Amado[1], Romeo Jr. L. Jorda[1], Lean Karlo S. Tolentino[1,2,3,4,5], and Lejan Alfred C. Enriquez[1,2,3,4,5]

[1]*Department of Electronics Engineering, Technological University of the Philippines, Manila, Philippines*

[2]*Integrated Research and Training Center, Technological University of the Philippines, Manila, Philippines*

[3]*Intelligent Systems, Applications, and Circuits Laboratory (ISAAC), Integrated Research and Training Center, Technological University of the Philippines, Manila, Philippines*

[4]*Data Analytics, Visualization, Information Driven (DAVID) Research Lab, Integrated Research and Training Center, Technological University of the Philippines, Manila, Philippines*

[5]*Center for Artificial Intelligence and Nanoelectronics (CAIN), Integrated Research and Training Center, Technological University of the Philippines, Manila, Philippines*

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***Abstract*—This study introduces a decision support system for optimizing stock portfolios. It employs a Hidden Markov Model for 95% accurate stock price forecasts over a five-day period. The system utilizes Quadratic Programming to refine allocation, focusing on up to 15 blue-chip companies. Key indicators like MACD, RSI, and Bollinger Bands offer clear buy, sell, or hold recommendations. It actively monitors the Philippine Stock Exchange, notifying users of significant deviations. Developed in Python and C#, both models were trained on a consistent 5-year dataset for reliable performance. Results show high prediction accuracy, averaging 98.923% (high price) and 98.741% (low price), benefiting investment strategies. The study compared SPOT-allocated portfolios to random ones, revealing a notable difference in profit/loss allocation. This underscores its value for informed and profitable decision-making in stock trading.**

Keywords*—Hidden Markov Model, Predictive Analysis, Quadratic Programming, Portfolio Optimization, Philippine Stock Exchange

I. INTRODUCTION

Stock is a part of the ownership of a company. Once a person becomes a shareholder, he shall have part of the profit, as well as the losses, the company makes. Stock market is volatile but the profit in investing against saving the money trumps the risks, especially on long term investments. Moreover, investing in stocks also drive businesses and economies as buying Initial Public Offerings (IPOs) from companies looking to expand could potentially create more jobs.

According to COL Financial, trusted stock trading platform in the Philippines, long-term investments on stocks yield more returns and protects investment from the effects of inflation[1]. While this could attract possible investors, there were only 772,187 market accounts registered with the 133 participating brokers in the Philippines in 2016. While there is an increase from 2015's 678,449 market accounts, the total stock traders are still less than 1% of the working population. Possible root causes could be the general lack of financial literacy or the pervasive myths regarding the stock market among the Filipinos. This could be a reflection of the Philippine economy in relation to its regional's peers, lagging behind [2].

This study will focus on the development of a system that will aid short-term stock traders by integrating a predictive model, a portfolio optimization algorithm and a news notification system. The evaluation will be conducted using blue chip companies, with each selected company equipped with a Continuous Hidden Markov Model (HMM) as a predictive tool, derived from historical stock price data on a daily basis. Each of the models for the 30 companies are assumed to be independent of each other. Furthermore, the models will be the basis of the portfolio optimization, hence, the effectivity of the latter depends on the model's accuracy.

The current event notification will be implemented using Messenger to maximize information mobility but is limited to disseminate only the headline and the link.

II. CONTRIBUTION

This research makes significant contributions in the domain of stock price predictions and portfolio optimization. The following points highlight the key contributions of this research, which collectively helps investors in making data-driven decisions.

- Integration of HMM with Quadratic Programming Techniques, which offers a unique approach to stock price prediction and portfolio optimization. Combining both methodologies would provide a new perspective on decision-making in financial markets.
- Our research demonstrates that the incorporation of the algorithm leads to more accurate stock price predictions compared to traditional models.
- Portfolio optimization ensures the creation of diversified portfolios that maximize expected returns for a given level of risk. A %P/L are displayed in the software's GUI.

By offering a concrete framework for stock price prediction and portfolio optimization, this study equips investors and financial professionals with a valuable toolset enhancing their investment strategies and decision-making processes.

III. RELATED WORKS

Vercher, et al. said that while the classical mean–variance model provides good results; fuzzy logic allows the trader to insert uncertainties and subjective characteristics on the database and models. They formulated two portfolio optimization problems which can be solved using linear programming [3].

Chang et al. determined that the genetic algorithm proves to be an effective and resilient method for handling challenging portfolio optimization tasks across various risk measures within a reasonable timeframe. As such, it represents an appealing investment tool for investors. It was concluded, as well, that cardinality constraints above one-third of the total assets should be disregarded, as they are dominated by lower Ks. They also provided clear evidence that smaller-sized portfolios could have a better performance than bigger ones [4].

Cura conducted a comparison of Particle Swarm Optimization with other well-known heuristic approaches. However, the study concluded that none of the methods, which include genetic algorithms, simulated annealing, and tabu search demonstrated a significant performance over other across types of investment policies, except in cases where PSO yielded better outcomes specifically in low-risk investments [5].

Meanwhile, Anagnostopoulos and Mamanis experimented with different algorithms to tackle mixed-integer (MI), multi-objective (MO) optimization problems. Their findings indicated that Strength Pareto Evolutionary Algorithm 2 (SPEA2) delivered the most favorable outcomes for both constrained and unconstrained MO optimization problems, with Pareto Envelope-based Selection Algorithm (PESA) following as the second-best option in terms of time efficiency. In general, all algorithms provided commendable approximations of the return-risk frontier [6].

Using Expectation-Maximization algorithm, Ahuja and Eksombatchai designed a model where weekly return is normally distributed. Subsequently, they assessed its performance in comparison to the Buy and Hold (BH) strategy and the Resistance and Support (RS) strategy. The outcomes revealed that the suggested HMM strategy demonstrated superior performance over the other two strategies in the majority cases [7].

Gupta and Dhingrahe developed a Maximum A Posteriori (MAP) estimator based on Hidden Markov Models (HMM), then contrasted with an Fuzzy Logic HMM model, ARIMA, and an ANN for stock forecasting. The results demonstrated that the MAP-HMM model exhibited superior performance for forecasting stocks of AAPL and IBM, while also showing comparable performance for DELL. Notably, the approach stood out for its simplicity when compared to other established methods [8]. Spark streaming which was used in Twitter messages in [9] can be considered also in stock market analysis.

Meanwhile, forty-five stock markets were classified in [10] using K-Means, Hierarchical, and Fuzzy C-Means where it was shown that the latter clustering is the most appropriate method. Also, ANN was utilized in [11] to predict a stock price of five certain companies.

Moreover, a random forest classifier and backtesting was utilized in [12] to predict stock price, with an accuracy score of 53.947%. Similarly, in [13] together with random forest, the author utilizes linear regression algorithm and Smo Regression for predicting stock prices, where the latter model shows the most effective in their study.

Social media was utilized in [14] as a factor for the stock market prediction. The author claims that it is one of the significant factors which drive the prices in the market. SVM and linear regression algorithms were used to predict the price in social media. Likewise, [15] utilized the SVM classifiers such as the logistic regression, SVC, and XGV classifier to forecast market prices in National Stock Exchange in India. While in [16] Gradient Boosting Machine (GBM) was utilized contrary to Naïve Bayes Algorithm, where GBM method is more efficient by 4.6%.

On top of that, Long Short-Term Memory (LSTM) was utilized in stock market prices for several researches in recent years. In [17] the author forecasts the stock prices of AAPL, GOOGL, and AMZN demonstrating their model's efficacy. Meanwhile, [18] investigates the robustness of LSTM model against variations in epochs and batch size, culminating in the development of a novel stock price framework. Moreover, a comprehensive analysis was conducted in [19] utilizing LSTM with ten years of historical stock price data from the National Stock Exchange (NSE) of India, with focus on the NIFTY 50 index. Similarly, in [20] LSTM was incorporated to the Colombo Stock Exchange portfolio management system, integrating stock price prediction capabilities, with a Brownian Motion algorithm-based model. Furthermore, while in [21] and [22] was complemented by the exclusive utilization of LSTM for stock price prediction, an added sentiment data analysis were leverage utilizing XGBoost and BERT Model, respectively.

IV. METHODOLOGY

In this paper, a decision support system was developed that provides users with the timing and the level of shares to buy, sell and hold to optimize their stock portfolios.

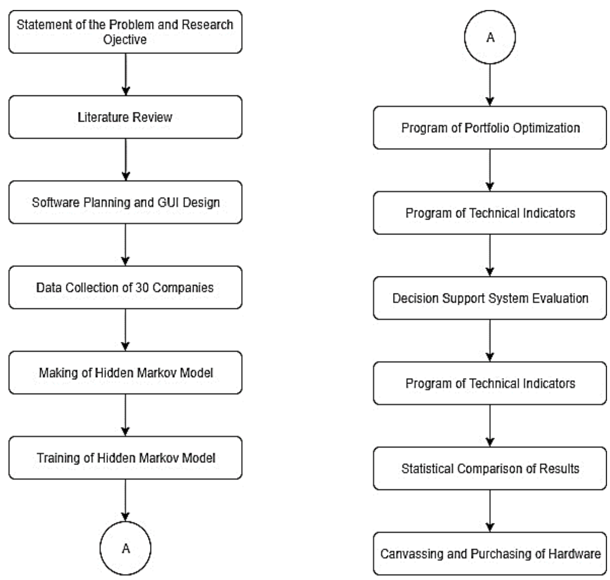

Fig. 1. System architecture's process flow

The system architecture's process flow is shown in fig. 1. The entire research journey starts with the articulation of the problem statement and the establishment of clear research objectives. This foundational step lays the foundation for the subsequent stages, providing a focused direction for the study. Building upon this, the process advances to a comprehensive literature review, delving into existing research and relevant publications. The next step includes software planning and GUI design, where careful consideration is given, ensuring an intuitive and efficient user experience.

Next, data collection from 30 companies is undertaken. The dataset forms the basis for the development of a Hidden Markov Model, a pivotal element in the system. Once the model is constructed, it undergoes a rigorous training process, which involves fine-tuning the parameters to ensure optimal performance in analyzing the collected data. Additionally, the program for portfolio optimization is developed, followed by the incorporation of technical indicators, enhancing the analytical capabilities of the system.

The decision support system is then evaluated, ensuring that it meets the defined research objectives and functions effectively. This step includes rigorous training and validation, which include a statistical analysis using t-test to assess the performance of the system.

A. Stock Price Prediction

The Hidden Markov Model (HMM) was utilized in this paper, as shown in fig.2, the critical component of the system.

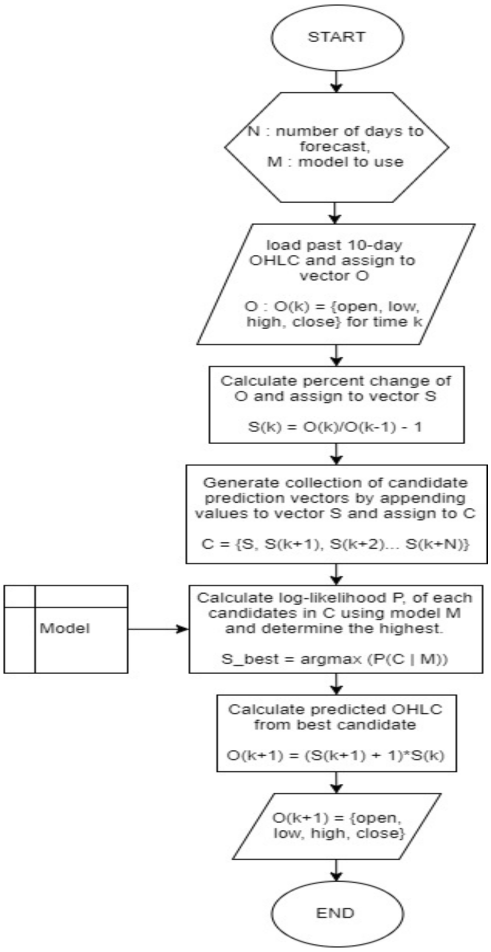

Fig. 2. Flowchart of Hidden Markov Model (HMM)

The open, max, min, and close stock prices for the last five (5) years of the thirty (30) blue chip companies were taken from Investing.com. These were fed to SPOT! which has an HMM that generates a model according to (1):

$$O_{t+1} = argma\,x\big(P(O_{t+1}, O_t, O_{t-1}, \dots, O_1|\lambda)\big) \quad (1)$$

Where O_{t+N} is the observation vector for the next N time step. Observation vector O_t refers to percent change $(Open, Low, High, Close)$ at time t from time $t-1$ wherein (2):

$$O_t = \begin{pmatrix} \frac{Open(t)}{Open(t-1)} - 1, \frac{Low(t)}{Low(t-1)} - 1, \frac{High(t)}{High(t-1)} - \\ 1, \frac{Close(t)}{Close(t-1)} - 1 \end{pmatrix} \quad (2)$$

$P(O_{t+1}, O_t, O_{t-1}, \dots, O_1|\lambda)$ is the probability of observation sequence $O_{t+1}, O_t, O_{t-1}, \dots, O_1$, occurring given model λ.

Probability of Observation O of an HMM with Gaussian Mixture Model (GMM) Emissions (3):

$$b(j) = \sum_{m=1}^{M} c_{jm}\, \mathcal{N}\big(O, \mu_j, \Sigma_j\big) \quad (3)$$

M is the number of components of GMM, c_{jm} is the weight of a GMM component under state j, $\mathcal{N}\big(O, \mu_j, \Sigma_j\big)$ is the probability of vector O under Gaussian Mixture Model, μ_j represents the centroid vector associated with state j, and Σ_j denotes the covariance matrix under state j.

SPOT! generates a model for each company and the user could choose up to fifteen companies to forecast for up to five days. However, companies with RSIs of under 40 on February 12, 2018 were chosen for the experiment.

$N = number\ of\ days\ to\ forecast$

$M = model\ to\ use$

The program loads the past 10-day open, high, low, close stock prices of the chosen companies and assigns it to vector O (4):

$$O : O(k) = \{open, low, high, close\}\ for\ time\ k \quad (4)$$

The percent change of vector $\boldsymbol{O}$ is calculated and assigned to vector $\boldsymbol{S}$ (5):

$$\boldsymbol{S}(k) = \frac{\boldsymbol{O}(k)}{\boldsymbol{O}(k-1)-1} \quad (5)$$

The program then generates a collection of candidate prediction vectors by appending values to vector $\boldsymbol{S}$ and assign to C (6):

$$C = \{\boldsymbol{S}, \boldsymbol{S}(k+1), \boldsymbol{S}(k+2) \dots, \boldsymbol{S}(k+N)\} \quad (6)$$

The log-likelihood P of each candidate in C is calculated by using model M and the highest probability is determined (7):

$$S_{best} = argmax\big(P(C|M)\big) \quad (7)$$

The predicted open, high, low, and close stock prices (8) are then calculated from the best candidates (9):

$$O(k+1) = \{open, low, high, close\} \quad (8)$$

$$O(k+1) = (S(k+1) + 1) * S(k) \quad (9)$$

B. Portfolio Optimization

The predicted prices are the input to the Portfolio Optimization (PO). The PO relies on Markowitz's Mean-Variance Optimization method, which identifies the efficient frontier of potential stocks based on their volatility, expressed as variance, and return, express as mean. The PO (10) employed is modified such that the expected returns the output of the forecast;

$$x_{optimal} = mi\,n\left(\frac{1}{2}x^T Cx\right) \tag{10}$$

With constraints (11):

$$\sum m_i x_i \geq r \tag{11}$$

Such that (12):

$$min(m) \leq r \leq max(m) \tag{12}$$

x is allocation vector, $x = (x_1, x_2, \ldots, x_N)$ for N stocks portfolio, C is the covariance matrix, m_i represents the predicted return of stock i whereas r signifies the overall return of the portfolio.

Through quadratic programming, the user may find the appropriate allocation that will minimize the risk for certain risk.

C. Testing and Evaluation

The program will be evaluated by two sets of experiment. The first experiment will involve the actual manipulation of two portfolios. The first portfolio will follow the suggestion of the program on the first day of the two-week period and was left unaltered on the remaining days of the experiment. On the second portfolio, cash will be distributed randomly among the companies and remain unaltered on the duration of the deployment. The result of these two portfolios were then compared.

The second experiment will run under simulation where there will be no financial restrictions. Two imaginary portfolios containing the same amount of cash and companies, differing only on the allocation of the assets will be used as subjects. The first portfolio will follow the suggestion of the program. The program will run for a two-week period and the portfolio allocation will be altered according to the day-to-day suggestions. On the second portfolio, cash will be distributed evenly among the companies and remained unaltered on the duration of the deployment. The result of these two portfolios will be then compared.

V. Results and Discussions

This section provides an overview of the outcomes derived from the methodologies outlined in section II. This section encompasses the presentation of the data collected pertaining to stock investments and allocations.

A. Predicted Max and Min Prices Generated by SPOT!

The max and min prices of each of the six (6) companies invested—Companies AGI, ALI, BDO, JFC, JGS, and MBT—were compiled by SPOT!. The software SPOT! was fed with the historical data of each of the companies available in Investing.com from January 2012 to January 2017.

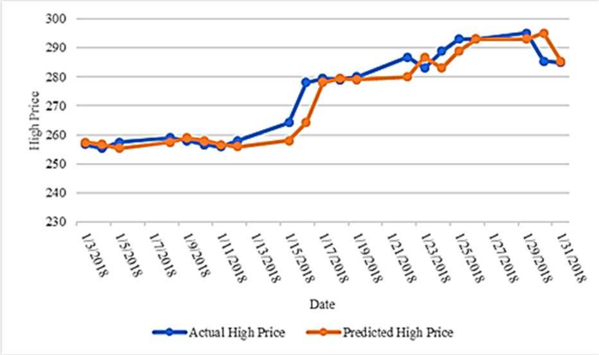

Fig. 3. Actual Max Price (Blue) vs. Predicted Max Price (Orange) for Company JFC

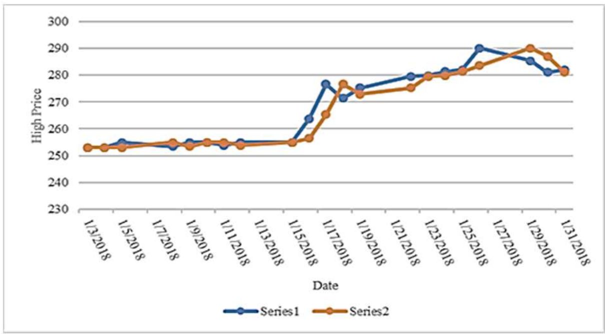

Fig. 4. Actual Min. Price (Blue) vs. Predicted Min. Price (Orange) for Company JFC

The line graphs of the actual and predicted max and mix price of JFC from January 3, 2018, to January 31, 2018, were shown in fig. 3 and fig. 4, respectively. SPOT! Predicts and present the max. and low prices. The actual values of prices can be seen in the website of Philippine Stock Exchange or in Bloomberg after the market is closed. The max and min percent error for JFC is 1.13187% and 1.0178%, respectively. Hence, SPOT! Provides 98.868% reliability (max price) and 98.982% reliability (min price). For validation of predicted values, t-test was used with a 5% level of significance, a degree of freedom of 40, and a t-critical value of 2.021075. The t stat value for the predicted high price is 0.286790. The null hypothesis is accepted since t stat value is within the negative and positive critical value. Hence, the predicted high price for JFC is acceptable. With respect to the predicted low price, the t stat value is 0.243087. The null hypothesis is accepted since t stat value is within the positive and negative critical value. Hence, the predicted low price for JFC is acceptable.

TABLE I. Average Percent Error for Each Company

Company	A.P.E. (Max Price) in %	A.P.E. (Min Price) in %
AGI	0.5396383	1.011651
ALI	1.154146	0.996912
BDO	1.162022	1.227169
JFC	1.131865	1.017785
JGS	1.192985	1.162608
MBT	0.881587	0.988766

TABLE II. % Reliability of Price Prediction for Each Company

Company	R.P.P. (Max Price) in %	R.P.P. (Min Price) in %
AGI	99.460	97.838
ALI	98.846	99.003

BDO	98.838	98.773
JFC	98.868	98.982
JGS	98.807	98.837
MBT	99.118	99.011

Similar findings were found in the other five companies. Table I shows the average percentage errors for the high and low prices of six different companies as predicted by SPOT!. These errors represent the accuracy of the software's predictions, with lower values indicating more accurate predictions. All predictions were validated using a t-test with significance level of 5%. Each prediction in companies stock prices (max and min) are accepted since each of t stat value is within the positive and negative critical value.

Furthermore, Table II summarizes the reliability of software's prediction for max and min prices of the six companies. The reliability percentages represent how well SPOT! Predictions match the actual market data.

B. Portfolio Organization

The results of the first experiment are shown in Fig.5, comparing the per day %P/L of the SPOT-allocated portfolio against the randomly allocated portfolio.

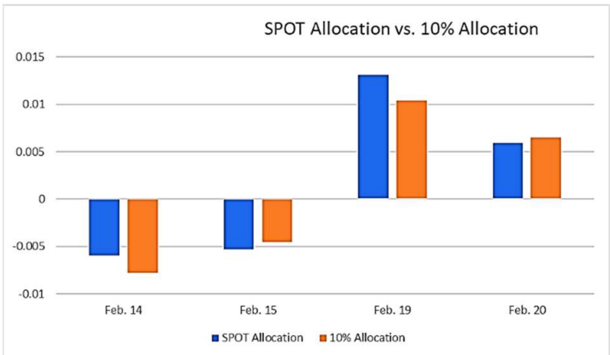

Fig. 5. Comparison of SPOT Allocation vs. Random Allocation

The simulated data for the minimum risk, maximum risk and an allocation of at most Php10,000 per company is shown below.

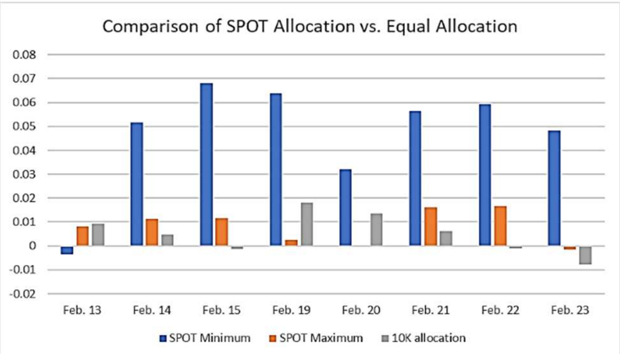

Fig. 6. Comparison of %P/L of SPOT Allocation vs. Php. 10,000 Allocation

TABLE III. %P/L COMPARISON OF SPOT ALLOCATION VS. 10K ALLOCATION

%P/L for SPOT min	%P/L for 10k allocation
0.003369567	0.009332168
0.051701475	0.004822093
0.068111164	0.001350186
0.063834004	0.018176455
0.032068268	0.013450803
0.056416783	0.006121222
0.059358635	0.000890669

Table I displays the average percentage errors for both maximum and minimum value of the respective companies from December 27, 2017, to February 2, 2018. Among them, AGI exhibits the smallest mean percent error in predicting high prices, while M demonstrates the lowest mean percent error in forecasting low prices using SPOT! Conversely, JGS records the highest mean percent error for both high and low-price predictions.

For comparison, the author employed a t-test determine whether there exists a notable distinction between spot allocation and random allocation, as illustrated in fig. 5. The calculated t-stat score is 0.126221, whereas the critical t-value is 1.94318. As the t-stat score is lower than the critical t-value, it indicates that the percentage profit/loss allocation for the two experiments does not exhibit a significant difference.

Furthermore, t-test was also employed to check if there is significant difference between the %P/L spot allocation and 10K allocation, see figure 6. The calculated t-stat score is 4.79485, while the critical t-value is 1.76131. Since the t-stat score surpasses the t-critical value, it indicates a significant difference in the %P/L allocation between the two experiments.

C. System Requirements

The SPOT! Software was already an executable file which can be run with a computer specification of at least Intel-i3 7th Gen., 4Gb RAM, and 500Gb of Storage.

D. Comparison of result with prior works on Stock Price Prediction

TABLE IV. SIMILARITIES, DIFFERENCES, AND ACCURACIES OF THE PRIOR WORK VS THIS WORK ON STOCK PRICE PREDICTION

Authors	Similarities	Difference	Acc. Rate
[12]	Program in python, dataset comes from online finance platform	Utilizes Random Forest Classifier and Backtesting as Model	53.947%
[14]	Stock price prediction	Utilizes Linear Regression, polynomial regression, and support vector regression, utilize social media, weight-based prediction, R language	72.32%
[15]	Forecast the Local Stock Exchange (India), Python programming, Utilize Open, High (max), Low (min), and Close price	Utilizes SVM classifiers such as logistic classifiers, SVC & XGB Classifiers	99%
[16]	Forecast the Local Stock Exchange (India), Utilize Open, High (max), Low (min), and Close price, utilization of statistical t-test,	Utilizes Gradient Boosting Machines Algorithm	92.3%
[17]	dataset comes from online finance platform	Uses LSTM DL Model	97%
[18]	Utilize Open, High (max), Low (min),	Uses LSTM DL Model, investigates	75%

	and Close price for forecasting	model's defenses against epochs and batch size	
[19]	Forecast the Local Stock Exchange (India), Mean Percent Error was computed	Uses LSTM DL Model, specific dataset for India stock market	83.88%
[20]	Forecast the Local Stock Exchange (Sri Lanka), Portfolio management system, with UI/UX development	Uses LSTM DL Model and Brownian motion algorithm, specific dataset for Colombo stock market	85% - LSTM 80% - Brownian motion algorithm
[21]	Mean Percent Error was computed,	Uses LSTM DL Model with XGBoost for sentiment analysis (news headlines and daily stock trends)	4.164% MAPE – LSTM 94.5% - XGBoost
[22]	Forecast the Local Stock Exchange (China), Mean Percent Error was computed	Uses LSTM DL Model with BERT model for with sentiment analysis (investor sentiment)	55.1%
This work	Utilizes Hidden Markov Model and applied in stock market (PSE), with real %P/L of software (SPOT!) allocation vs. 10,000 Philippine Peso allocation		98.923% (HMM)

VI. Conclusion

This research effectively aids Filipino stock investors and traders in determining optimal buying and selling strategies to maximize profits. Additionally, it demonstrates the ability to forecast high and low prices for the following day with a minimal mean percent error of 2.372% and a maximal mean percent error of 2.136%, showcasing superior accuracy compared to prior studies, which achieved a mean percent error range of 2.29623% to 2.08381% using Artificial Neural Networks (ANN). The acceptability of the maximum and minimum predicted values for each of the chosen five (5) blue-chip companies is proven by t-test. In addition, the study has a real-time notification system through RSS which alerts the stock trader about the important events about the companies invested. The project is made through and almost of Python and requires secured internet connection for real-time consideration for update of data and events.

The study's findings and results indicate that the HMM can provide acceptable forecast for stock prices on the following day. However, error increases as the forecast range increases. The SPOT-allocated portfolio performed better than the 10% allocation under the condition that all assets were successfully bought. The technical indicators have been helpful in the decision support system of SPOT! Python's numpy and pandas libraries proved to be helpful for the determination of these indicators. The event notification system helps in informing users about the current events in PSE.

Recommendations

The proponents would like to give the following recommendations to further improve the project and for future reference of work:

- Utilize other predictive models other than Hidden Markov Model to improve accuracy in stock price prediction and forecast time.
- Incorporate the user's actual portfolio in the software to have easier access to the presentation of the fluctuations in the stock market.
- Add more technical indicators that will help as a basis when to buy, sell, and hold stocks.
- The inclusion of user's portfolio-related filters in the events notification system.
- Conversion of the software into a web application

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