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Efficient Machine Learning Algorithm for Predicting Market Prices for Electronics Modules

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Abstract

Pricing research in the marketing realm has primarily focused on branded products.The required quality of electronic modules (e.g., packaged electronic devices) is evaluated in electronics manufacturing through qualification testing using standards and user-defined requirements. The electronics industry faces a challenge in that product qualification testing is time-consuming and expensive. The current Ethiopian market is still run in a traditional manner, with market drivers not being used to forecast future market prices and to evaluate the data in order to predict future market prices. Furthermore, the analysis methodologies were frequently manual, resulting in inefficiencies in market prediction time and quality. The study looks at current Ethiopian market parameters to see which ones are most useful for predicting market price. The study also examines the efficacy of four machine learning models to anticipate Ethiopian commodity market prices. The experiment involved comparing models using distinct train and test data that had strong individual prediction performance and low redundancy. In the models (Support Vector Machine (SVM), Artificial Neural Network (ANN), K-Nearest Neighbor (K-NN), and Ensemble Learning), the performance of ANN and Ensemble Learning algorithms has been shown to be more accurate than SVM and K-NN.The ANN model's average MAE rate was 2.8084. With average MAE rates of 4.9362 and 8.1178, Ensemble Learning and SVM come in second and third, respectively. With an MAE rate of more than 45.3381, the other model was the worst performer.

Keywords: 1. Feature selection 2. Price prediction 3. Machine Learning 4. electronics module 5. Ethiopian market

1. Introduction

This study contributes to the small body of literature on commodity pricing. Commodity pricing has not received much attention in the realms of marketing because pricing in marketing has primarily focused on the issue of pricing branded products rather than homogeneous products such as commodities.Pecht, M., Shibutani, T., Kang, M., Hodkiewicz, M., & Cripps, E. (2016)predict that the global market for electronic products will reach US$2.4 trillion per year by 2020. This expansion has resulted in fierce competition among manufacturers to reduce product time-to-market and cost while delivering high-quality, dependable products to their customers.By gathering and analyzing various market data, modern marketing systems routinely conduct market prediction utilizing various analysis approaches Subha, M. V., &Nambi, S. T. (2012).

It has been dubbed the "harvest of a business" because all other marketing efforts are solely focused on sowing the seed for business success, which is accomplished through revenue generated by pricing. T.T. Nagle and R.K. Holden (1995). Pricing is the only component of the marketing mix that generates revenue for the company. As a result, little is known about the pricing process. G. Avlonitis and K. Indounas (2006). Few studies on the pricing of mature industrial products have been conducted. Haley, G., and S. Goldberg (2008) discussed the fundamental reasons for changing or maintaining prices.

Fundamental, technical, and quantitative analysis are three methodologies that are often used to anticipate the price for a given market. The fundamental approach looks at the economic elements that influence a market's price. These various market drivers provide data that indicates current market price characteristics and assists in forecasting future market price characteristicsCaley, J. A. (2013). Based on the attribute of items, technical analysis aids in anticipating what others are thinking technical indicators are calculated using past prices and volumes in technical analysis. The calculated numbers are then utilized to forecast future price fluctuations. By identifying patterns from noisy data and visually studying the goods charts, technical analysis can also identify regularities.The third technique, quantitative, is more quantitative and statistical, allowing the rules to be easily programmed into a computer or machine. Statistical arbitrage, automated trading, and electronic market creation are some of the approaches used in this type of analysis. With statistical market models, quantitative analysis is more effective at replacing the human element of trading. W. Huang, Y. Nakamori, and S. Y. Wang (2005).

This paper investigates the predictability of future Ethiopian market prices, allowing government and non-government institutions in the sector, as well as individual traders, to perform market activities with little risk. Market activities can be carried out on a daily basis with a clear understanding of market prices. Predicting future market price conditions allows you to select what product you need to make, when you need to make it, and how you want to approach the market Caley, J. A. (2013). Despite the fact that such systems can be appreciated to some level, sufficient data analytical activities are not used to predict future market price scenarios, resulting in market uncertainty. Traders are still looking for market analysis that can predict future possibilities and lower risk. To accurately investigate the data, we can encode it into technical indicators, which can then be classified using well-known classification techniques. One way to overcome the problem is to learn from other countries' experiences while utilizing computational algorithms. Patterns in data can be found using computational methods. The results of the computer methods can subsequently be utilized to forecast future market prices in Ethiopia. The study's goal is to uncover market characteristics that influence Ethiopian market price forecasting.

Furthermore, it investigates various computer strategies that are more effective in predicting market price in Ethiopia. The SVM, ANN, K-NN, and Ensemble Learning are the four machine learning models chosemore reliablein predicting future Ethiopian market prices. Data from various governmental and non-governmental sectors will be evaluated in order to produce a more accurate forecast of Ethiopian market pricing. The overall goal of this research is to assess existing market data and forecast market prices for important marketed commodities in Ethiopia and the specific purpose he most valuable market features for forecasting future market price in Ethiopia, and choose which machine learning model best meets the market condition and Ethiopian market price prediction.

2. Materials and methods

Using Machine Learning models, researchers have been working on market data analysis and market price prediction. The overview covers the four selected models (SVM, ANN, K-NN, and Ensemble Learning) as well as other hybrid models, genetic Algorithms, and other algorithms that have been used to predict market movements.For classifying a problem given a set of features, there are numerous machine learning algorithms available. Machine learning algorithms have been investigated and used for high frequency trading and market microstructure data. U. Thissen, R. Van Brakel, and A.P. de Weijer (2003).

Support Vector Machines (SVM)

Kim employs a method similar to KNN, he employs a SVM for classification Kim, K. J. (2003). Twelve technical indicators are generated from the Korea composite stock price index to be used as input variables. Kim investigates which parameters perform best for the stock data. SVM was discovered to be sensitive to the values of its parameters, and when the correct parameters were chosen, SVM outperformed the BPN and KNN classifiers in experimental tests Das, S. P., &Padhy, S. (2012) investigate two machine learning techniques for predicting futures trade prices in the Indian stock market: Back Propagation Technique (BP) and Support Vector Machine (SVM). The study makes use of data gathered by the Indian Stock Exchange (NSE).

Normalized mean squared error (NMSE), mean absolute error (MAE), and directional symmetry are the performance metrics used (DS). The NSME for all futures stock indexes taken into account ranges from 0.9299 to 1.1521. The MAE ranges from 0.2379 to 0.3887, and the last cnidarian DS ranges from 55.17 to 91.2512. The results show that SVM outperforms BPN. With the help of SVM, Shen, S., Jiang, H., & Zhang, T. (2012) attempted to develop a new prediction algorithm that exploits the temporal correlation between global stock markets and various financial products to predict the next-day stock trend. They use various stock market indexes from around the world as input features for next-day stock prediction. They looked at each index to see how well it predicted the next day's stock market. They discovered that the DAX, Germany's stock index, was more accurate than the other stock indexes for single feature prediction, with an accuracy of 70.8 percent. The results show that SVM performs best for four selected features with an accuracy of 74.4 percent, while MART performs best when all available features are used (73.9 percent). Finally, they create a new model that uses the output of SVM prediction to make marketing rules and decisions.

An SVM places the bold line as far away from the closest observations of the two classes as possible, maximizing its margin. The prediction that it finds far from the middle line is the most accurate. In the real world, it is not always possible to obtain a line that perfectly separates the data within the space. As a result, we may need to use a curved decision boundary. It is possible to obtain a hyper-plane that can separate the data, but this may not be desirable if the data contains noise. In such cases, the soft margin method must be used Lean Yu, Huanhuan Chen, Shouyang Wang, & Kin Keung Lai. (2009).

K-Neighborhood (K-NN)

K-Neighborhood (K-NN)isone of the most basic machine learning algorithms is the K-Nearest Neighbor (KNN) classifier Huang, W., Nakamori, Y., & Wang, S. Y. (2005).The KNN algorithm predicts the classification of a new sample point by using a database in which the data points are separated into several separable classes. The closest examples of an object are used to classify it. Any distance metric and a majority vote can be used to perform the measurement Karazmodeh, M., Nasiri, S., & Hashemi, S. M. (2013). The other issue here is determining which observations in the database are similar enough to our new observation for us to consider their classification when classifying the new observation Shen, S., Jiang, H., & Zhang, T. (2012). The Euclidean distance is one of the most widely used metrics. The following formula calculates the Euclidian distance between two instances (X_1, X_2, X_3...X_n) and (U_1, U_2, U_3....U_n).

$$\sqrt{(X_1 - U_1) + (X_2 - U_2) + \cdots (X_n - U_n)} \qquad (1)$$

Where X_1, X_2, X_3, and X_n are predictors of the first instance and U_1, U_2, U3, and U_n are predictors of the second instance.

Subha, M. V., &Nambi, S. T. (2012) attempted to create a market trading model that can profitably trade market securities while outperforming buy-and-hold. For classifying daily stock market data, 12 technical indicators, 54 features, and 10 macroeconomic data indicators were developed in the study. The data used was obtained from Yahoo Finance and spans the years January 1, 2001 to January 1, 2010. For prediction, this system employs the K-NN and SVM classifiers. The results showed that the KNN model-based strategy outperformed the buy-and-hold strategy in 7 of the 10 stocks. In terms of prediction, K-NN outperformed the SVM model. Khan, Z. H., Alin, T. S., & Hussain, M. A. (2011) forecast Bangladesh Stock Exchange market index values with a reasonable degree of accuracy using ANNs.

They used a back propagation algorithm for training and a Multilayer feed-forward network as a network model for price prediction. The General Index (GI), Net Asset Value (NAV), P/E ratio, Earnings per Share (EPS), and Share Volume were discovered to be inputs influencing share price. Using only two inputs from ACI Pharmaceutical Company's past historical data, they predicted stock values for the future 8 days of November 2010 using the back-Propagation algorithm and were able to compare the predicted values to the actual values. The simulation's average error was 3.71 percent.They forecasted stock values for the next 8 days in November using past historical data from ACI Pharmaceutical Company and only 5 inputs. The average error in the simulation was 1.53 percent. They conclude that the greater the amount of input data available, the better the training and the more accurate the results. Adebiyi, A. A., Ayo, C. K., Adebiyi, M., and Otokiti, S. O. (2012) used a hybrid approach to improve stock price prediction accuracy. The hybrid model combines variables from technical and fundamental analysis. A neural network predictive model was then developed for stock price prediction.

The back-propagation algorithm was used to train three-layer (one hidden layer) multilayer perceptron models (a feed-forward neural network model). To train the network, the hybridized approach employs identified 18 input variables, which include both technical and fundamental analysis variables. The hybridized approach resulted in the most accurate daily stock price prediction of the 18-24-1 back-propagation network (BPN). The hybrid approach combines variables from technical and fundamental analysis. Finally, they conclude that the hybridized approach has the potential to improve stock market decision making by providing more accurate stock prediction than the existing technical approaches.

Artificial Neural Networks (ANNs)

S., & Berry, M. J. (2011). Because of its ability to learn, ANN is widely used in literature patterns that are complex. When using artificial neural networks, it is difficult to find parameters that learn from training data without overfitting (i.e., memorizing the training data). The system may overfit the current data if there are too many hidden nodes; if there are too few, the system may fail to properly fit the input values. The stopping criteria could be based on the total error of the network falling below a predetermined error level. G. S. Linoff and M. J. Berry (2011).

Ensemble methods

Ensemble methods are learning algorithms that build a set of classifiers and then use a weighted vote to classify new data points Dietterich, T. G. (2002). Bayesian averaging is the original ensemble method, but more recent algorithms include error-correcting output coding, bagging, and boosting. The first method employs manipulation of the training example to generate multiple hypotheses Trybula, Walter J. (1997). The learning algorithm is repeated several times with a different subset of the training examples each time. This technique is particularly effective for unstable learning algorithms whose output classifier changes dramatically in response to small changes in the training data. The second method modifies the set of input features that the learning algorithm can use Dietterich, T. G. (2002). The method works best when the input features are highly redundant. The third method modifies the y values provided to the learning algorithm Trybula, Walter J. (1997).

The relabeled data from the subsets is then fed into a learning algorithm, which can then build the classifier. The final approach introduces randomness into the learning algorithm Dietterich, T. G. (2002). Narayanan, B., & Govindarajan, M. (2015) used a time-based data set to forecast the stock market price more precisely than previous models. For analyzing time-based data sets, the paper employed classifier techniques such as Support Vector Machines and Nave Bayes. They also used an ensembles model, which increases classification accuracy by combining multiple classifiers. The boosting method improved the accuracy of the given algorithm.

Hybrid Vehicles

Tsai, C. F., and S. P. Wang (March 2009) created a model that combines an Artificial Neural Network (ANN) and decision trees to improve prediction accuracy in a stock price forecasting model. Fundamental and technical analyses are used as indicators in a hybrid model that predicts stock prices in Taiwan's electron industry. The dataset was retrieved from the TEJ database, and 53 variables were selected.In terms of performance, the results show that the hybrid model outperforms the individual models. Caley, J. A. (2013) investigated the predictability of financial movement direction using SVM. Macroeconomic inputs, the stock market index, and the exchange rate are examples of input features.Yahoo Finance and the Pacific Exchange Rate are used to collect historical data. The results show that SVM takes the lead based on individual performance. The combined model of the four approaches, on the other hand, achieves the best results.

Genetic Algorithm

Karazmodeh, M., Nasiri, S., & Hashemi, S. M. (2013) used Improved Particle Swarm Optimization (IPSO) based on Support Vector Machines in their research. They were successful in forecasting stock indices. PSO is an evolutionary computation technique that works similarly to how birds travel when looking for food, or how a fish school will behave.The behavior was modeled in such a way that the "particles" within the "swarm" (or population) are regarded as solutions to a given problem. They combined this algorithm with SVM to create the hybrid model IPSOSVM. As a feature, technical indicators and stock market indexes are used. According to the results, mutation in particles resulted in higher accuracy because the particle always searches the entire state space, preventing mistakes of not finding the other best options in other possible states. The hybrid model was discovered to be more effective than the individual models (PSO and SVM).

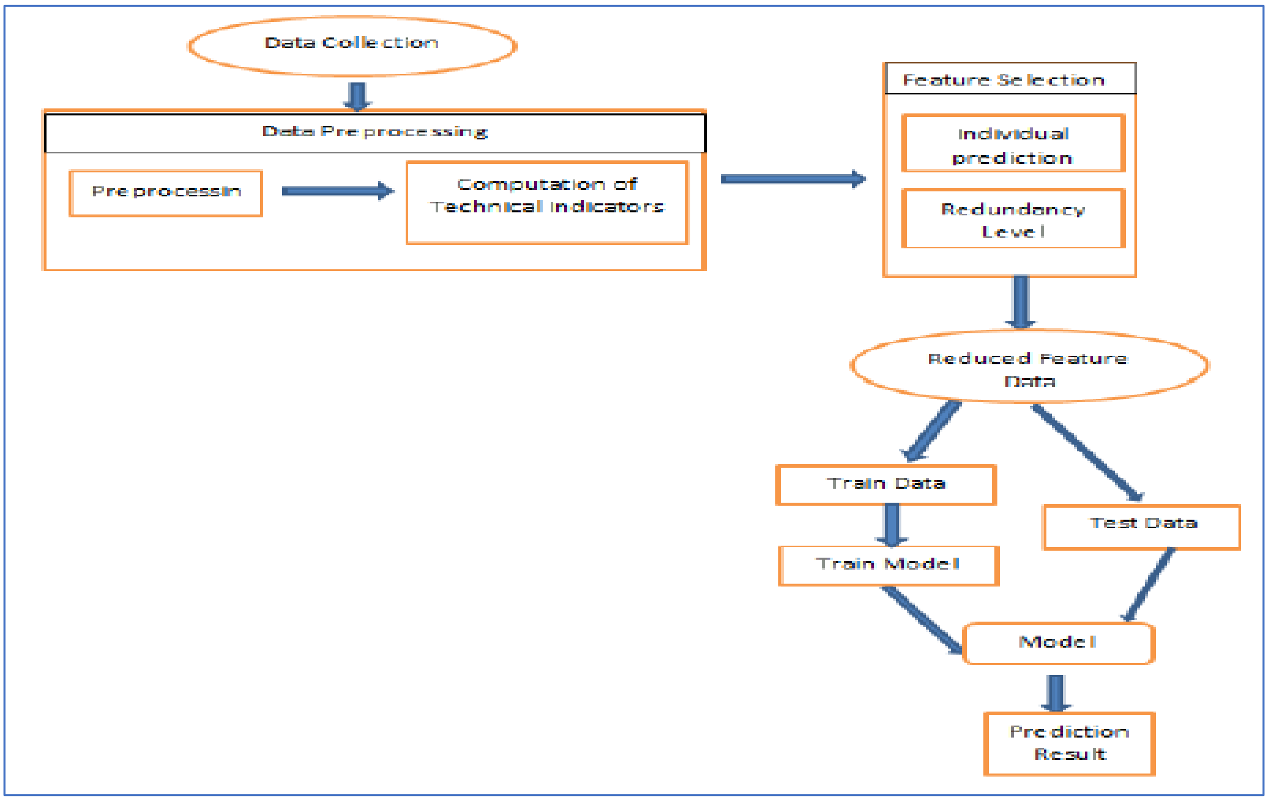

Figure 1.Depicts the proposed methodology

Figure 1 depicted the proposed methodology's direction. The proposed methodology begins with data collection, after which the data is preprocessed and technical indicators are computed. The newly formed dataset was fed into the feature selection process. The features that were chosen were then used to train and test the four machine learning models. Finally, the models were compared, and the best predictive machine learning models were used to forecast commodity prices.

Data collection

The following attributes: trade date; lowest price (low), highest price (high), volume (ton), opening and closing price of Bluetooth, power bank, and mobile charging module. To ensure the dataset's relevance, the data attributes were compared to various standard datasets and stock market indexes used for prediction. Interpolation of missing values was used to overcome the effect of the data gap caused by the market closing on weekdays.The data includes the daily opening and closing prices of Bluetooth, power bank, and mobile charging module. The experiment makes use of historical prices for the three commodities from 2008 to 2016. The data set contained 94,993 rows, with power bank module accounting for the vast majority of the records (roughly 72,160). There are 18,021 rows of mobile charging module and 4,812 rows of Bluetooth, respectively.

Model Selection for Machine Learning

The goal of this studyis to analyze existing market data and forecast market prices using computational algorithms. Thestudies to determine which machine learning technique is more accurate in predicting future Ethiopian market opportunity and price. Various machine learning algorithms were investigated throughout this work, and the most effective ones were used to find patterns in the data. Each machine learning model's performance was evaluated using valuable features extracted from the dataset during the feature selection stage. The best performing algorithms were then chosen based on their accuracy in making predictions and their consistency in performance. SVM, K-NN, ANN, and Ensemble Learning were the machine learning techniques.

Cross validation by tenfold

We used the Weka 10-fold cross validation method for training and testing. This means that the dataset is divided into ten parts, the first nine of which are used to train the algorithm and the tenth is used to evaluate the algorithm. This procedure was repeated, giving each of the split dataset's ten parts a chance to be the held-out test set.

Separate the training and testing sets

A separate training and testing set were created and used for the study. Data from various years will be included in the test set but will not be used for training.

Metrics of Performance

Various metrics will be used to assess the applicability and performance of the aforementioned Machine Learning techniques. The effectiveness of classification algorithms can be affected by a variety of factors such as the quality of information provided by the attributes, the class distribution of the dataset, and the number of instances. Weka classification, which is available in the Weka Explorer GUI, is used for machine learning models. There are seven types of classifiers, including functions, lazy, and tree classifiers. The functions category includes models such as the ANN and SVM. The lazy model includes the K-NN model. The Ensemble Learning model is found in the final one.

3. Results and Discussion

A market's accumulated data can provide us with the majority of the information we need to formulate and direct future markets, as well as see different market opportunities.We examine the performance of a selected prediction algorithm using the results of feature selection.

3.1 **Comparison of Machine Learning Models**

Weka 3.8.0 is used for the experiments to predict the data on the three commodities, four Machine Learning models (SVM, ANN, K-NN, and ensemble Learning) were used (power bank module, mobile charging module, Bluetooth module). These evaluations are carried out using the features selected during the feature selection stage.From fig.2,3,4 and 5 comparison of machine learning algorithm with highly predictive features (10-fold cross validation)

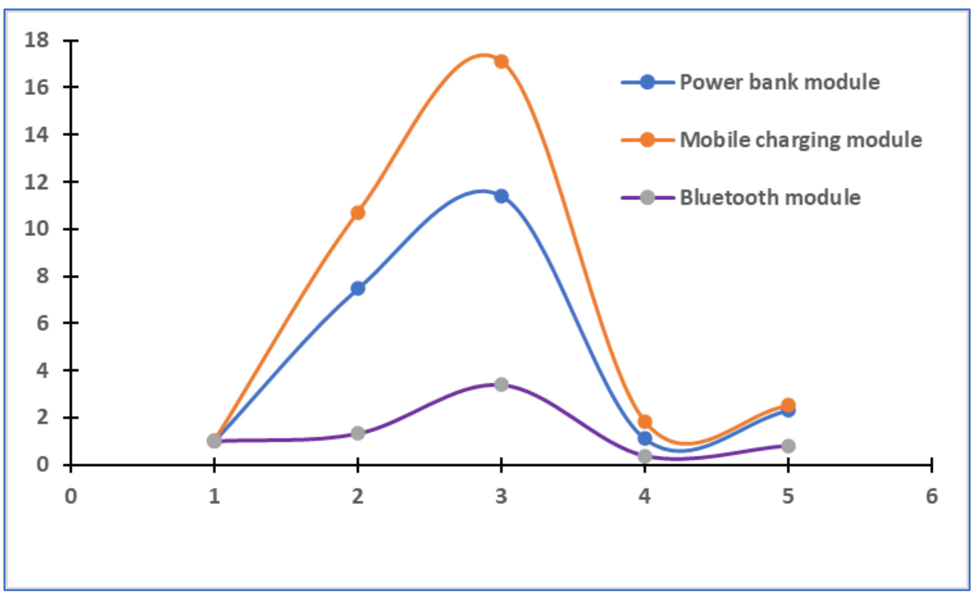

Figure 2. SVMmachine learning algorithm with highly predictive features

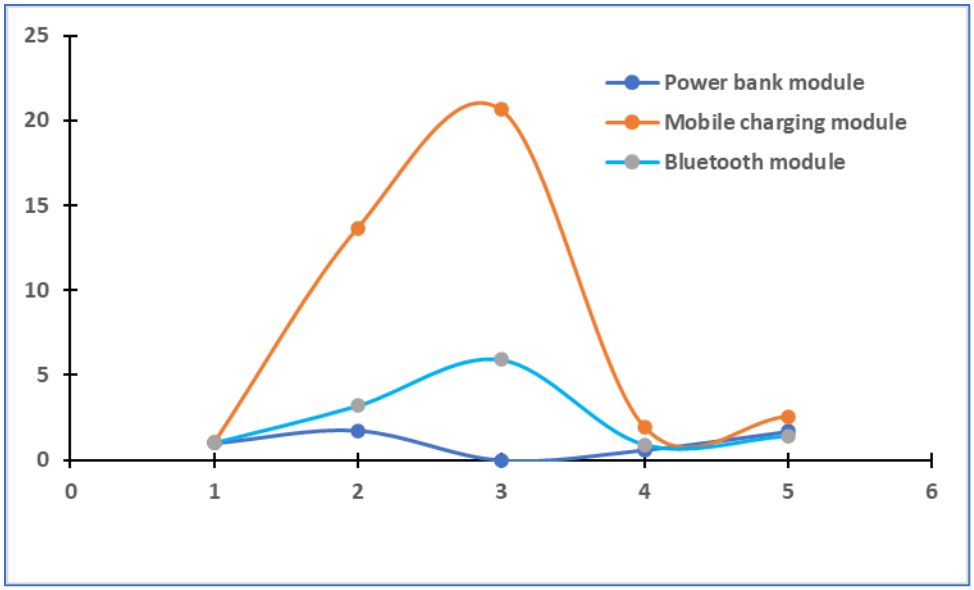

Figure 3. ANNmachine learning algorithm with highly predictive features

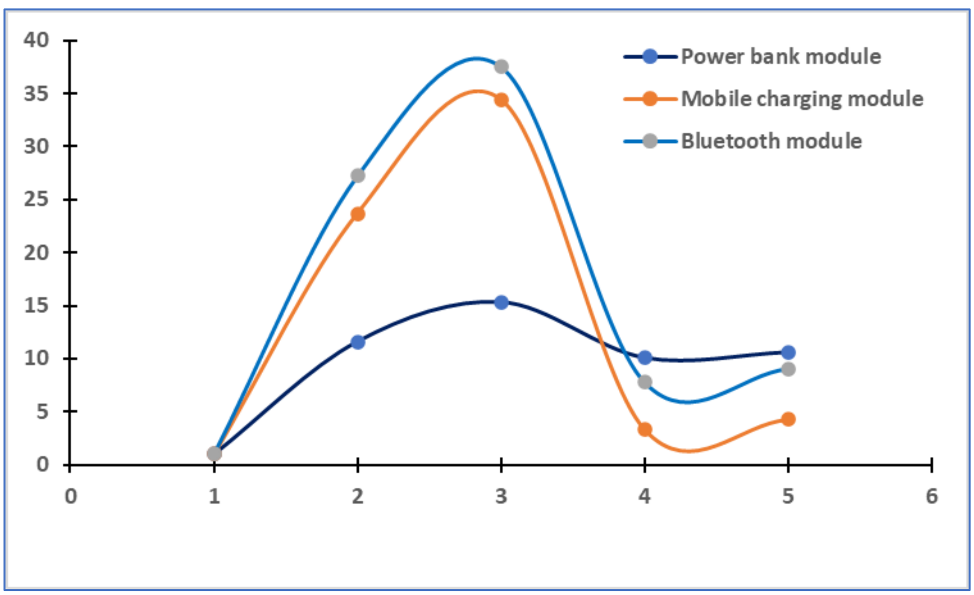

Figure 4. KNNmachine learning algorithm with highly predictive features

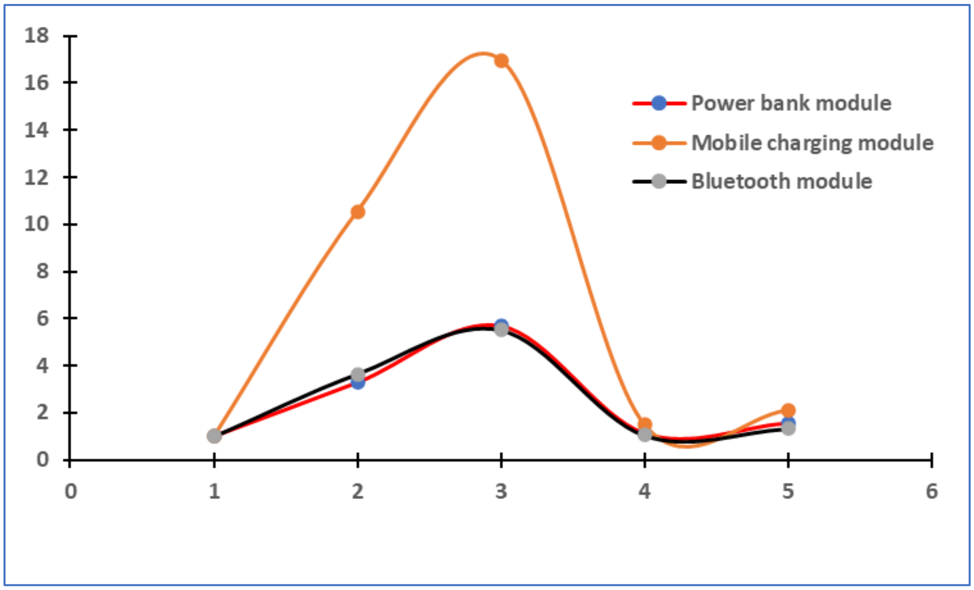

Figure 5. Ensemble Learningwith highly predictive features

According to the 10-fold cross validation results, Ensemble Learning prediction had the lowest MAE Value of 5.8243, followed by ANN (6.1945) and SVM (6.5017). In contrast, the machine learning algorithm K-NN recorded an extremely high MAE (20.8365), indicating that the model has the least predictive ability to forecast the price of the market commodities under consideration. The Ensemble Learning prediction results were consistent with all three commodities and also showed a moderated MAE when compared to the other models, whereas MAE values were not consistent across commodities.

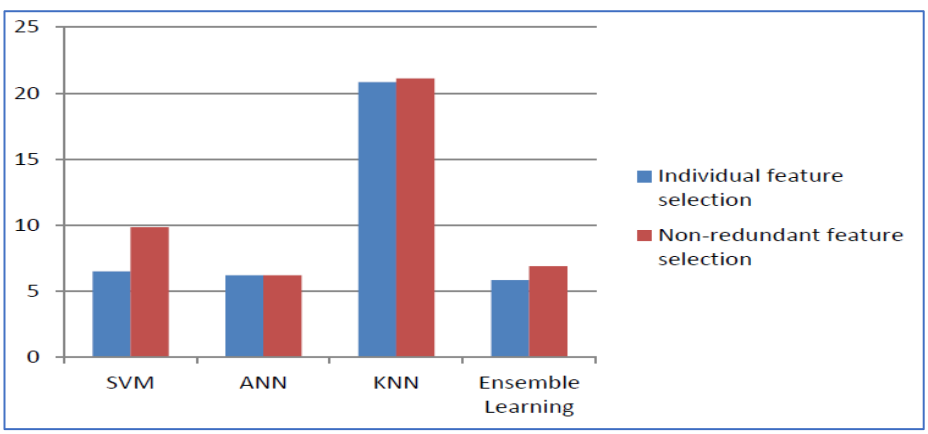

Figure 6. Shows a comparison of individual and non-redundant feature selection for 10-folds cross validation.

Separate trains and test sets were created in this section for the experiment to test the prediction models (fig.6). The test set included data from different years that had not been used for training. In the comparison of prediction models for power bank module and pea bean, 84 percent of the data was used for training and the remaining 16 percent for testing, whereas the proportion for mobile charging module was 74 percent for training and 26 percent for testing. Because of the differences in the amount of data collected, the proportions for the three data sets differ.

Table 1.Comparison of machine learning algorithm with highly predictive features (separate train and test data)

Machine Learning models	Performance matrix	Power bank module	Mobile charging module	Bluetooth module	Average MAE
SVM	Correlation coefficient	0.9873	0.9992	0.9998	
	Mean absolute error (MAE)	11.5981	9.9888	2.7667	8.1178
	Root mean squired error	18.5323	14.2259	5.2227	
	Relative absolute error	3.1473	1.5739	0.354	
	Root relative squired error	4.1032	2.176	0.6429	
ANN	Correlation coefficient	0.9999	0.9998	0.9997	
	Mean absolute error	1.2166	5.6839	1.5248	2.8084
	Root mean squired error	3.7112	8.561	5.7375	
	Relative absolute error	0.4201	0.8626	0.1951	
	Root relative squired error	1.0184	1.1054	0.7063	
KNN	Correlation coefficient	0.9935	0.9946	0.9351	
	Mean absolute error	29.7984	33.7384	72.4777	45.3381
	Root mean squired error	39.2275	47.2856	88.6036	
	Relative absolute error	11.7035	5.1199	9.1146	
	Root relative squired error	11.1156	8.1055	10.7325	
Ensemble Learning	Correlation coefficient	0.9999	0.9997	0.9996	
	Mean absolute error	3.3094	7.2889	4.2103	4.9362
	Root mean squired error	4.9128	10.9571	6.3391	

	Relative absolute error	1.1426	1.1061	0.5295	
	Root relative squired error	1.3481	1.4148	0.7679	

We calculated the average MAE for the four models across the three commodities using Table 1. The average MAE for SVM was 8.1178, 2.8084 for ANN, 45.3381 for K-NN, and 4.9362 for Ensemble Learning. The results for the ANN prediction were consistent across all three commodities, with a moderate MAE of 2.8084 when compared to the other models. Furthermore, using the ANN prediction model, power bank module had the lowest MAE value of 1.2166, while pea bean had the second lowest value (1.5248).

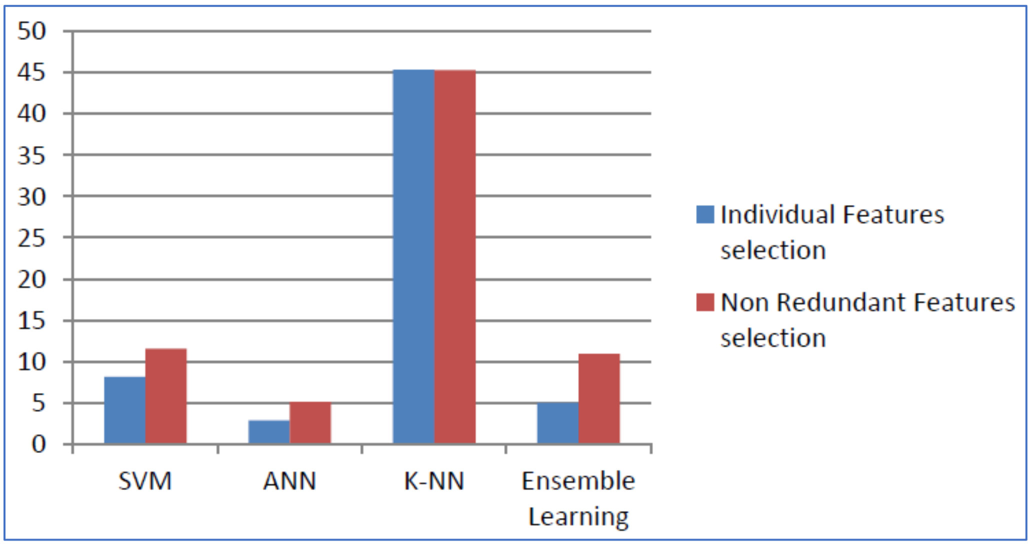

Figure 7. Illustrates a comparison of individual and non-redundant feature selection for a separate train test set.

The performance of the top ten features from individual feature selection outperformed non-redundant features for the SVM, ANN, and Ensemble Learning, as shown in Fig 7. The difference was insignificant for the model K-NN. On average, the features from Individual feature selection are superior to non-redundant features.The four machine learning models were analyzed and applied to commodity price data in this work. On commodity market data, the ANN model performed the best, while the K-NN model performed the worst.

The performance of Ensemble Learning and SVM is comparable. The average MAE for the models ANN, Ensemble Learning, and SVM is 5.0733, 7.1445, and 8.9902, respectively. It may be difficult to make a direct comparison of our work to other literatures. The majority of the literatures used a combination of stock market indexes, macroeconomic inputs, and technical indicators. Due to the lack of macroeconomic inputs and the absence of a stock market, our work was limited to technical indicators. Furthermore, the prediction of market price was not studied in the country side.Despite the fact that the three models, ANN, SVM, and Ensemble Learning, have significant performance in the area of financial time serious data prediction around the world Kandananond, K. (2011), Padhy, N. P. (2004) and Wilder, J. W. (1978).

3.2 ANN and Ensemble Learning Prediction Values

The results of the experiments shown in the preceding section separate the three models (ANN, Ensemble learning, and SVM) with the least MAE difference. The analysis of variance revealed that the MAE values for these prediction models were significantly different (p=0.05).Meanwhile, ANN, Ensemble Learning, and SVM can be used to predict commodity prices because the MAE value difference between them is insignificant. In the current study, the market price for the next five days was predicted using the top two models, ANN and Ensemble Learning. The highly predictive features were used in the prediction because they performed better than less redundant features (figures6 and7).The price prediction results for the three commodities, namely the power bank module, mobile charging module, and Bluetooth module, are shown in figures 8, 9, and 10.

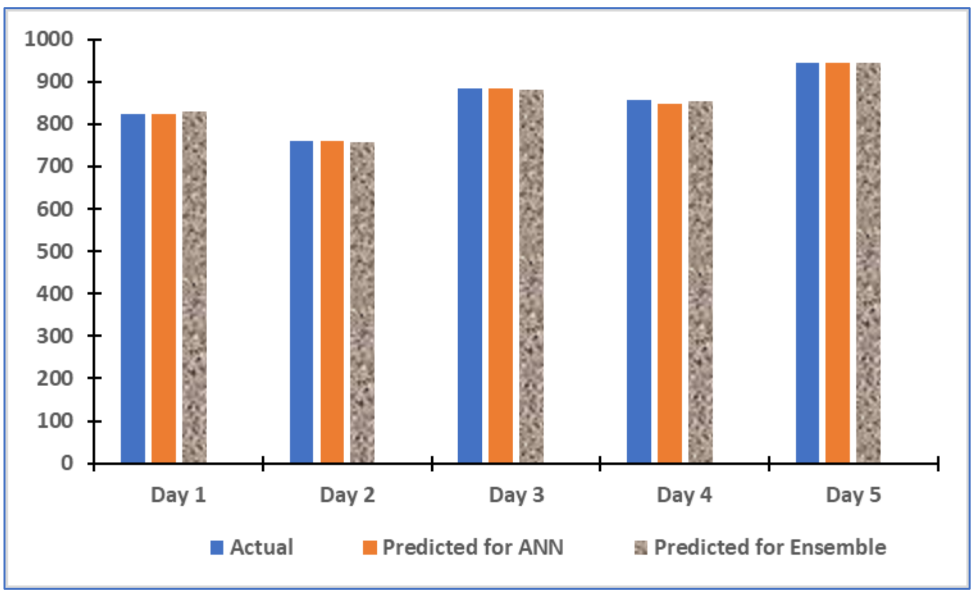

Figure 8. Power bank modulePrediction

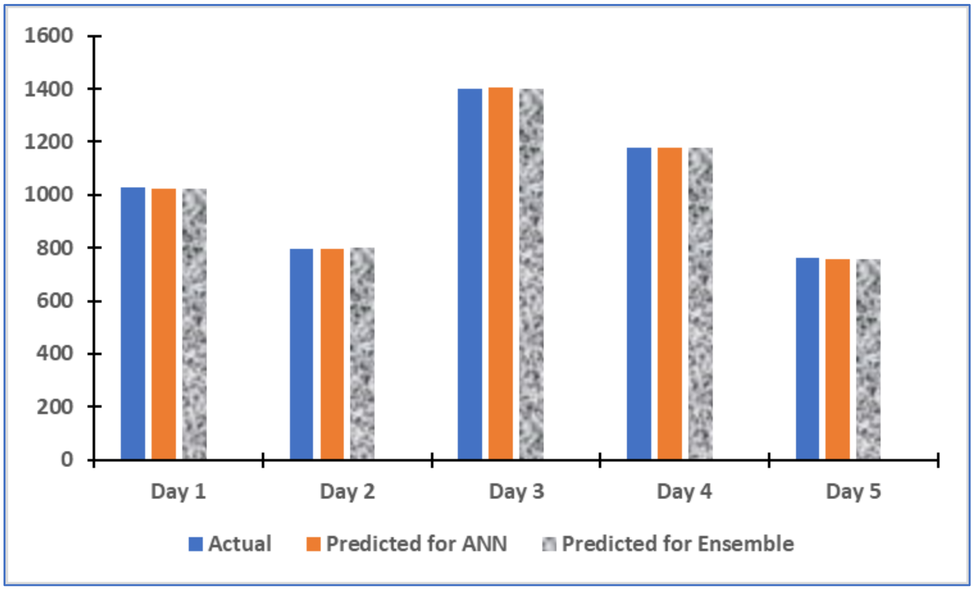

Figure 9. Mobile charging modulePrediction

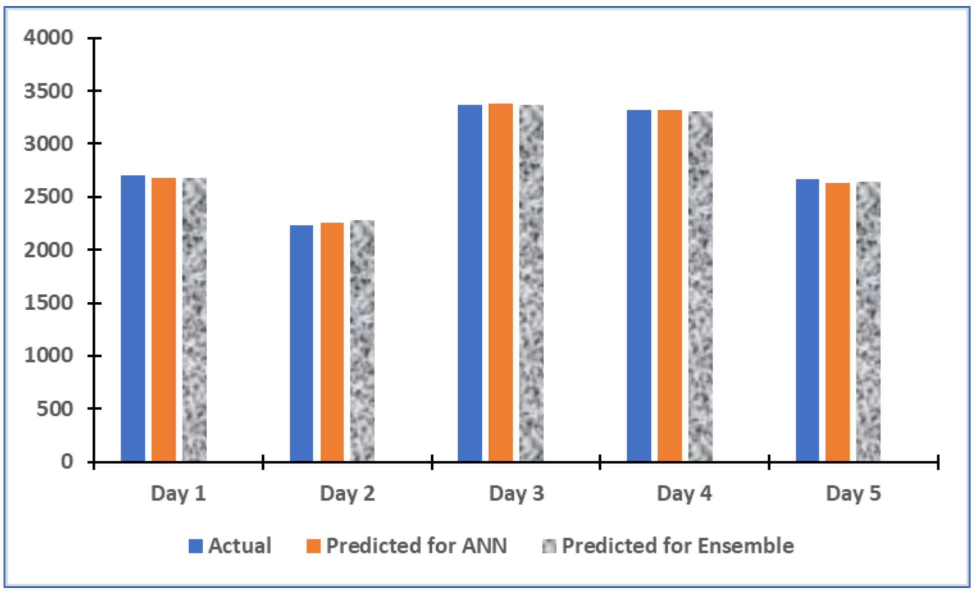

Figure 10. Bluetooth module Prediction

4. Conclusion

The proposed test optimization strategy's time and cost savings were successfully demonstrated using datasets from real qualification tests on the electronics module. The paper investigated current market attributes in order to identify the most valuable features for machine learning models that can better predict market prices. The performance of the ANN and Ensemble Learning algorithms outperformed SVM and K-NN among the models (SVM, ANN, K-NN, and Ensemble Learning). The ANN's average MAE rate was discovered to be 5.0733. Ensemble Learning and SVM come in second and third, with MAE rates of

7.1445 and 8.9902, respectively. With an MAE rate of 33.2964, the K-NN model was the worst performer.

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