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Advanced Classification Technique to Detect the Changes of Regimes in Financial Markets by Hybrid CNN-based Prediction

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Abstract

Traders' tactics shift in response to the shifting market circumstances. The statistical features of price fluctuations may be significantly altered by the collective conduct of traders. When some changes in the market eventuate, a "regime shift" takes place. According to the observed directional shifts, this proposed study attempts to define what constitutes between normal and abnormal market regimes in the financial markets. The study begins by using data from ten financial marketplaces. For each call, a time frame in which major events may have led to regime change is chosen. Using the previous returns of all the companies in the index, this study investigates the usage of a CNN with SVM deep learning hybrid to anticipate the index's movement. The experiment findings reveal that this CNN model can successfully extract more generic and useful features than conventional technical indicators and produce more resilient and lucrative financial performance than earlier machine learning techniques. Most of the inability to forecast is due to randomness, and a small amount is due to non-stationarity. There is also a statistical correlation between the legal regimes of various marketplaces. Using this data, it is conceivable to tell the difference between normal regimes and lawful regimes. The results show that the stock market efficiency has never been tested before with such a large data set, and this is a significant step forward for weak-form market efficiency testing.

Keywords: Convolutional Neural Networks, classification, deep learning, market prediction, SVM, statistical approach

1. Introduction

Efficient markets, defined by their ability to properly and swiftly incorporate new information into pricing through trade, are a major source of the advantages of free markets.

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As a result of the market's efficiency, every further information is completely unforeseeable and hence impossible to forecast. Due to the unpredictable nature of price changes in inefficient markets, relying on prediction algorithms is pointless. The goal of this research is to go from basic statistical analyses of market efficiency to models that use deep learning neural networks [1-5].

1.1 Old records of financial market

In financial markets, prices serve as a record of transactions. Traders may need to switch up their trading tactics in response to major political or economic developments. That might have a big impact on their collective behaviour, which is known as "regime change" in the market by academics. Thus, regime changes may be understood as variations in the financial market due to the rate fluctuations of any stock market.

1.2 Time series statistical analysis

Analyzing the statistical features of time series [6] is a typical strategy for identifying a regime transition. Here, the volatility of the market is measured over a period of time. It is reasonable to assume that regime shifts have occurred if the level of volatility has changed considerably over time. It is therefore possible to characterize financial price changes using a directional shift rather than time series. As opposed to time series, the data under this technique is most suitable to detect the changes of regimes in financial markets. Moreover, the changes of data point are estimated through time series analysis by statistical procedure. The data point are set as threshold value to predict the specific changes of the ups and downs in financial stock market rate reflection [7, 8]. On the other hand, directional shift and time series take different tacks on the same data. The directional change series may thus be used to identify regime shifts.

1.3 Changes of financial market

In this part, the explanation about the recognition of regime transition has been discussed. The aim is to categorise a sequence of variations of regimes over a period during transactions. The original data is the market's raw data, which records each and every transaction. Transactions occur randomly, which makes the analysis a difficult task. Most individuals prefer to sample data at regular intervals, such as every minute, every hour, or every day. For academics, this makes up the familiar time-series. In this statistical series data, two samples from two different rate of same stock market are captured during the sampling procedure. As a result, certain price swings may go unrecorded entirely. An alternative sampling method is directional change [9-13]. Directional change, on the other hand, is driven by data rather than time. Retroactive sampling procedures are used to shift the price details from the adjacent direction of trends with predefined threshold value to get new data. Traders are familiar with bull and bear markets, by the way the market is divided into uptrends and downtrends. Therefore, the extreme points of a time series are constantly sampled in order to ensure that no market fluctuations are overlooked [14, 15].

1.4 Motivation of this research

Time-series analysis is used in most studies of regime transitions, but not always. A number of models have been created to simulate regime shifts. These models were designed to keep tabs on changes in asset values. In other words, a regime transition is concluded when the mean, volatility, and correlation patterns of asset values drastically shift. These models have been shown to accurately predict market behavior in a short period of time. The hybrid model may provide a good and precise categorization of the financial market. Due to the time series sampling used in these regime-switching models, major changes in transaction prices may be missed. Hence, a time series in which all extreme points are considered is adopted.

2. Organization of the Research

The study paper is divided into various sections that detail the different processes that comprise the proposed framework for financial market prediction as a whole. Section 3 summarizes previous studies on financial market forecasting at a worldwide level. Section 4 presents the suggested framework for financial market forecasting. Section 5 provides performance metrics for the different experiments. Section 6 concludes this study project by discussing the probable future tasks.

3. Preliminaries

A variety of machine learning algorithms were compared by Li and Tam who predicted momentum and reversal effects through witness momentum of reversal. These forecasts are used to boost interest rates or to encourage contrarian trading [16].

According to Plaekandaras et al., the machine learning approach may be used to predict oil prices, currency rates, national stock indices, and gold prices using the geopolitical risk index suggested by the Federal Reserve. The GPR index accurately predicted the gold prices, but not other asset values. According to the authors, these negative outcomes are valuable because they caution against overreacting to intervention measures [17].

Das et al., employed machine learning to forecast future movement directions in order to test market efficiency theories. Deep learning (multiple-layer neural networks) was fed by the returns of individual equities in the S&P 500 index. A reasonable forecast of the S&P 500's future path was possible, but there was not enough data to rule out market efficiency [18]. To better understand volatility clustering in the financial market, Ma and Delahaye developed a novel technique that records whether or not a subsequent higher-than-median return occurs, rather of relying on standard autocorrelation methods on daily returns. Scholars then added a set of goals and restrictions to their model based on the MV and SD models [19].

Arditti [20] explains that in financial economics, skewness is critical. It pursued the mean-variance-skewness model studied and developed by Yu et al., [21] and Bhattacharya et al., [22]. Pouya et al., [23] have recently added two new goals to the core model: the P/E criteria and the suggestions of industry experts on market sectors. The sector capitalization limits are taken into account by Soleimani et al. [24]. Improvements standard models have more widespread use in real-world investment scenarios.

4. Methodologies

This research proposes a novel approach to forecast financial assets with stock market prediction of risk as a leading indicator. Instead of using terrorist attacks and wars as dummy variables, it uses the geopolitical risk indicator provided in numerous research works as an alternative to the usual technique in the literature. Since it is a continuous variable rather than a discrete (dummy) variable, this index covers a wider concept of geopolitical risk. It uses prominent international newspapers' word counts connected to financial market tensions to create monthly stock market risk indices of each country for the intraday transaction [25-29].

4.1 Time series analysis for financial information

Financial information is directional. To put it in another way, financial market traders engage in buy-and-sell transactions with the goal of making a profit. Once the transaction prices have been recorded, the foundation for financial information is laid. Although transactions occur at random times, there may be numerous transactions in a second and then no transactions in the next. As a result, the irregularity of transaction data makes it difficult to draw any conclusion from it. To summarize the data point, the proposed time series monitor over a period that has collected various data points. The "daily closing price" and "opening price" is a matter of change in regimes, for example the price at the end and starting of each trading day. Thus, financial data is summarized using time series analysis.

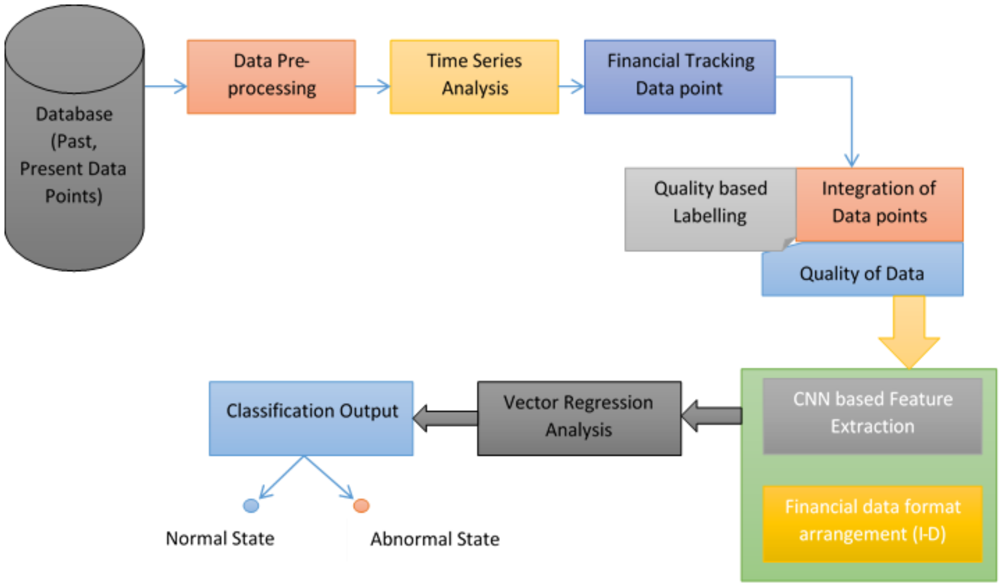

Figure 1. Proposed framework to predict regimes states (normal or abnormal)

4.2 Pre-Processing for Financial Tracking Data

In this proposed pre-processing framework, financial data tracking is summarized using a different method based on the idea of directional shifts [28]. The observer or monitor will assess the substantial changes in the data point while summarizing the data. The "Threshold" is the term used to describe the significant percentage shift in stock change. Data points are captured whenever the price crosses the threshold and moves in the opposite direction of the existing trend. This tracking procedure takes place in two parts such as, quality of data and its labeling work.

4.2.1 Quality of data

Data gaps in the raw financial trading data cause significant losses in the back test experiments. There may be a correlation between current price and volume, and future price trends, but this is not an indicator for the direction that the prices may take a day later. It is also detrimental to the training process because there is a mismatch between the label and the data point's intrinsic information. Therefore, an effective pre-processing strategy is developed to overcome this problem.

4.2.2 Labeling

The results of these experiments show that supervised training based on three-class labeling strategy achieves the best results in finance and machine learning benchmarks. But this labelling strategy cannot distinguish more precise classes, such as violent surge, moderate rise, crash, and the edge of down. As a result, this execution plan explores and evaluates the effects of a more finely tuned labelling method.

4.3 CNN feature extraction

Many domains, including computer vision and natural language processing, have found CNN to be a useful model for automatically extracting features. However, regular convolutions are not directly supported by the financial data format. Even though financial trade records can be arranged into two-dimensional frames, typical two-dimensional convolutions are inadequate because convolutions of diverse data kinds may produce illogical results. On the other hand, in order to avoid obtaining absurd results as in two-dimensional convolution scenarios, the usual single-dimensional convolution is opted since data of each kind needs parameter sharing while simultaneously requiring unambiguous bounds [30-33]. An unique single-dimensional convolution architecture known as "cross data type one-dimensional CNN" is proposed to solve this issue. As shown in Figure 1, the proposed framework for the entire dimension of feature maps is reduced by a max-pooling layer after each convolutional layer.

4.4 Vector Regression by SVM Classifier

In the area of artificial learning, the Support Vector Regression (SVR) technique, that is regression-based vector machine operation called as Support Vector Machine (SVM) is used. Economic and financial experts have been interested in the SVR's capacity to better characterize nonlinear and stationary processes than other econometric approaches. Error words play no part in this suggested framework and are ignored if they do not exceed an established criterion, which seeks to mimic real data observations [34]. There are penalties only for mistakes that go beyond that. Through a minimizing method, Support Vectors (SVs) are identified as the data points that define the provided "error tolerance band".

5. Results and Discussion

The proposed approach predicts the future price movement every two hours and then makes trading choices based on the forecast result. The two-hour time interval in this architectural paradigm is two-fold. When using convolutions, the longer the time interval, the larger the data sequence needed for the convolution. Single-dimensional convolution is applied to each of the 24 consecutive 5-minute data sets. The stock exchange datasets supplied in this proposed model have the same time period to provide fair comparisons between the maximum likelihood prediction and single-dimension models. Figure 2 shows the training and testing attributes with fit line (model fit) for all.

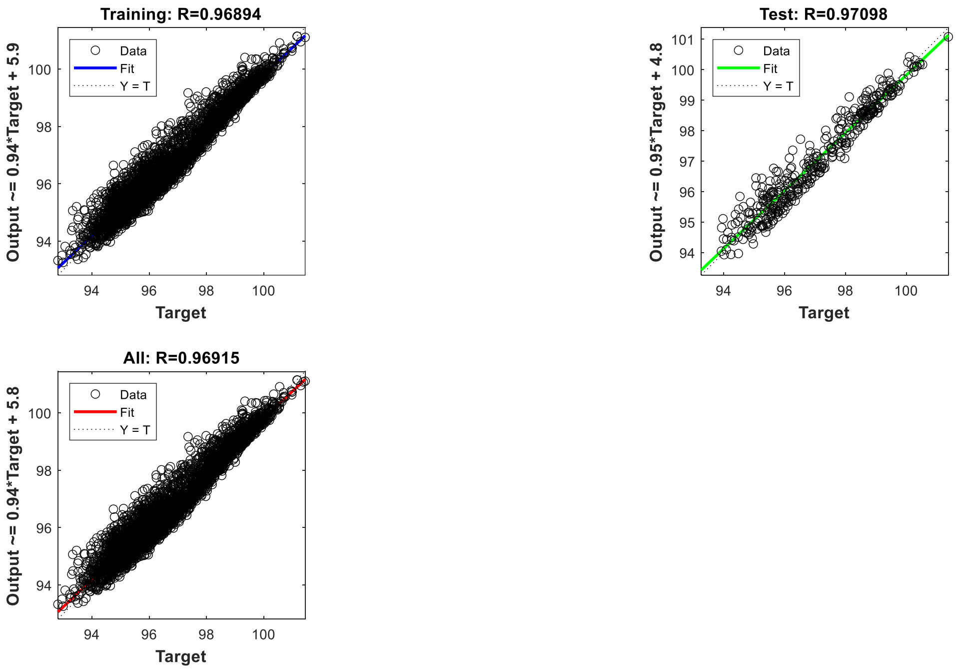

Figure 2. Obtained output results of predicted normal and abnormal conditions

In general, the price change of a product over a shorter period of time is significantly lower than the price change over a longer period. Similarly, the market's minor fluctuations over a two-hour period are equal to the average price change for that time frame. It is thus less profitable to trade for short periods of time when slippage and transaction costs are taken into account. The correlation between input and error is shown in figure 3.

The accurate predictions measuring through performance metrics of the proposed architecture named as mean absolute percentage error is calculated. In all models, the dependent variable's initial lag is taken into account for higher accurate prediction. In addition to training models of greater lag order, it also yields results that are statistically comparable. It is used to measure the accurate model performance through statistical training by Bayesian regularization approach. The obtained results are shown in table 1.

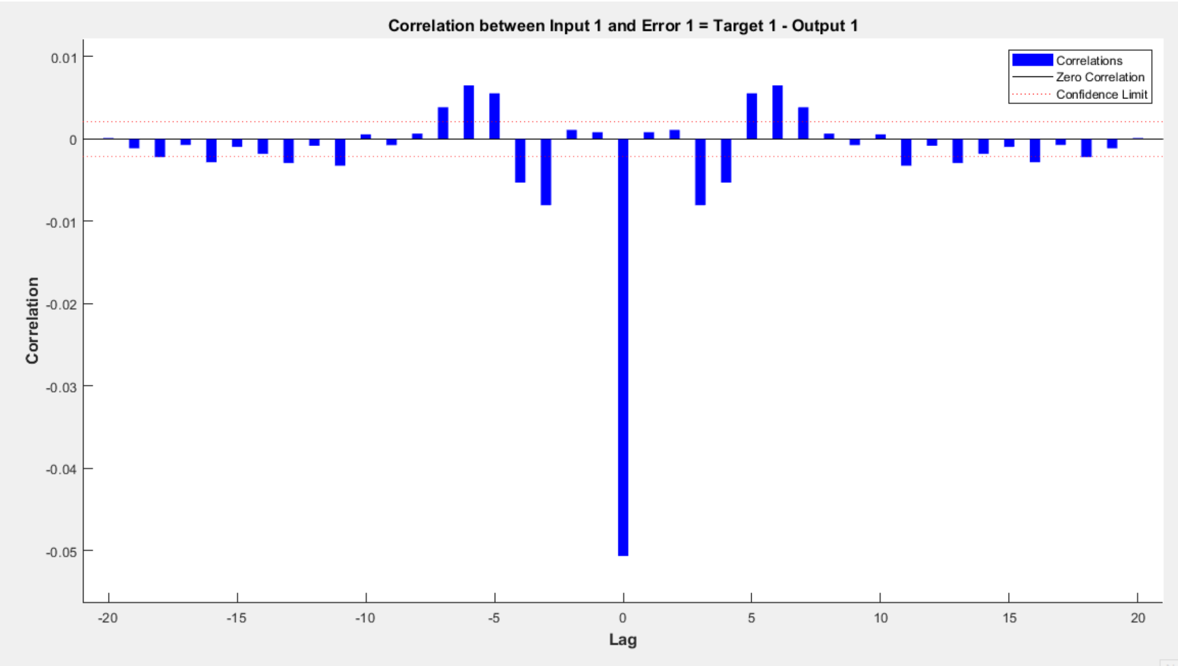

Figure 3. Correlation between Input and Error

Table 1. Obtained results during performance

Model Prediction	Target Values	MSE	Regression
Training	3200	1.70107e-1	9.68943e-1
Testing	400	1.59748e-1	9.70977e-1
Validation	400	0	0

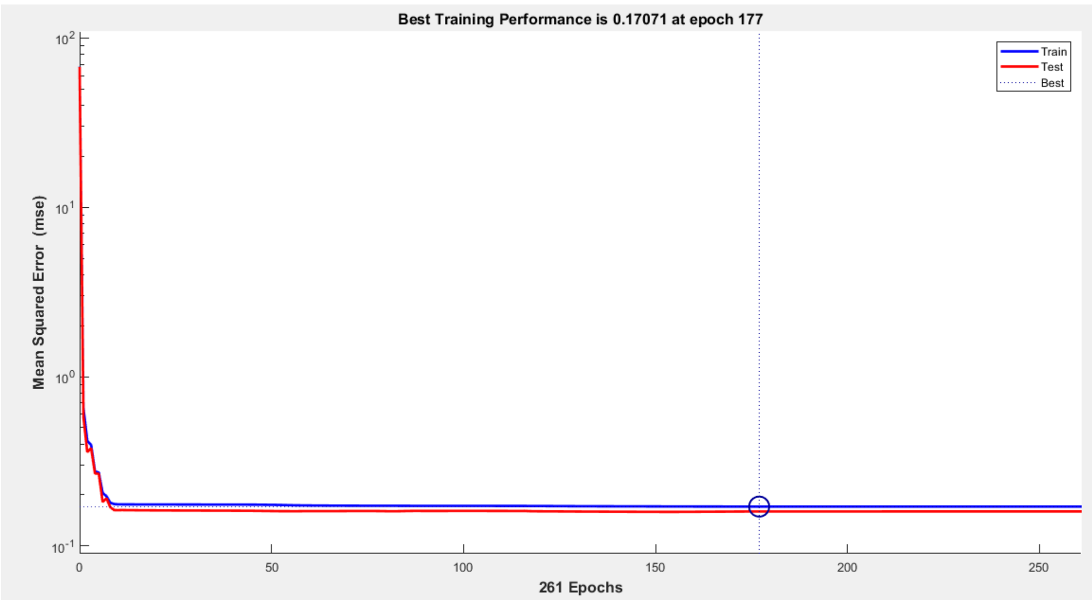

Figure 4. Best training performance data point

This proposed model is trained and tested for results observations in each phase. It assesses the predicting ability for the projections of 1, 3, 6, 12, and 24 months based on the trained model. In order to train the neural networks through lots of epochs to predict higher accuracy, the past changes in stock markets have to be observed as long as the selection continues. Finally, it is found that the proposed training model has the best training performance at epoch 177. The mean squared values are computed and shown in figure 4.

6. Conclusion

The proposed and developed hybrid convolutional neural networks and SVM technique for market prediction have been created in the domain of share market. The extracted data directly from financial trade data archives using this tool. The results of the back-test suggest that the proposed model is capable of extracting broader and useful aspects than those represented by the standard technical indicators. It has also been shown to surpass earlier machine learning algorithms in average yearly return on investment by a significant amount. Additional architectural tweaking is found to be hypothesized and lead to an improved predictability, although this needs further investigation. The paper concludes by advocating future research into neural net designs that may be better suited and optimized for this prediction challenge. One way to address these issues with a single-objective investment strategy is to look at the second-order stochastic dominance constraint-based multi-objective portfolio optimization strategy. Experiments also indicated that the model's performance is directly tied to the benchmark used. As a result, this may be focused on in the upcoming investigation.

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