Deep Learning and Time Series-to-Image Encoding for Financial Decision Prediction

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Abstract—**In the last decade, market financial forecasting has attracted high interests amongst the researchers in pattern recognition. Usually, the data used for analysing the market, and then gamble on its future trend, are provided as time series; this aspect, along with the high fluctuation of this kind of data, cuts out the use of very efficient classification tools, very popular in the state of the art, like the well known convolutional neural networks (CNNs) models such as Inception, ResNet, AlexNet, and so on. This forces the researchers to train new tools from scratch. Such operations could be very time consuming. This paper exploits an ensemble of CNNs, trained over Gramian angular fields (GAF) images, generated from time series related to the IBM stocks; the aim is the prediction of the future trend of the IBM stocks. A multi-resolution imaging approach is used to feed each CNN, enabling the analysis of different time intervals for a single observation. A simple trading system based on the ensemble forecaster is used to evaluate the quality of the proposed approach.**

I. Introduction

Nowadays, the research in this time series area is one of the most active amongst the pattern recognition related topics, and at the same time it is one of the most challenging. This is mainly due to the fact that stock prices are often influenced by factors which are quite hard predictable like political events, the behaviour of the other stock markets and, last but not least, the psychology of the investors these aspects tend to model the market as an entity which is dynamic, non-linear, non-parametric, and chaotic. So researchers developed several neural networks alongside the artificial neural networks (ANN), also the machine learning approaches had the possibility to show their efficiency through the years. The authors have compared the capabilities of the support vector machines in market prediction related issues against those obtained by using the radial basis function (RBF) networks and back propagation (BP). A recent literature review is performed, which compares the modern machine learning approaches in financial forecasting field. Interesting results have also been obtained when fusing together the above described techniques: as an example, the authors have fused ANN with decision trees (DT). The rationale behind this hybrid approach is that where ANNs are able to provide quite good performances in forecasting the market trend, a DT model is stronger in generating potential rules which describe the forecasting decisions. Similarly, a two-stage fusion approach is proposed for predicting CNX Nifty and S&P Bombay Stock Exchange (BSE) Sensex from Indian stock markets. Specifically, the first stage uses a support vector regression (SVR), whereas the second one exploits, in turn, ANN, random forest, and SVR. Ten indicators have been selected as input to the prediction models. In general, however, predicting the daily direction (positive or negative) of the market requires to solve a classification problem, whereas directly predicting the profit needs to address a regression problem. Moreover, "there is no general consensus on best forecasting technique for price prediction", particularly since "price series is inherently a non-stationary series having non-constant mean and variance", making it not always advantageous to represent the problem through linear models such as regression. Furthermore, the actual trend of the research seems to be oriented towards the analysis of the data in their raw forms, therefore as time series, without doing any dimensionality changing. Inspired by recent successes of supervised and unsupervised learning techniques in computer vision, and with the aim to change this trend, in this paper we propose a trading system based on the forecast of the daily direction of a market index by exploiting the discriminatory capabilities of the convolutional neural networks (CNN) when dealing with GAF images. Indeed, CNNs has shown very good accuracy results when applied to pattern recognition on image and video data. We encoded time series as images to allow machines to visually recognise, classify and learn structures and patterns. Reformulating features of time series as visual clues has raised much attention in computer science and physics. Model training, evaluation and testing are executed on IBM stocks future. Time series of the future prices are processed in a twofold way: firstly, different intervals of time are considered, in order to analyse the same trend under different points of view; then, GAF images are built for each of the defined time intervals. Therefore, the main contributions of the proposed approach are as follows. • The proposed system exploits the GAF imaging approach for encoding time series data as images; • The composition of GAF images in a multi-resolution structure helps improving the market prediction results; • The classification phase is carried out by organising in an ensemble a set of CNNs which have the different architecture, and used cost sensitive learning approach to deal with data imbalance. • Comparisons both with state of the art baseline approaches (e.g., buy-and-hold (B&H) strategy) have been performed, showing that the proposed system is capable of obtaining a higher profit in the same investment period.

II. Literature Survey

Ye Zhang et al. explored ways to conver time series data to a multi-scaled signed recurrence plot for classification using Fully Convolutional Networks. Experimental results on 45 UCR datasets demonstrate that the proposed method outperforms the state-of-the-art, and each block of MS-RP is also demonstrated hierarchically through validation experiments. Z Wang and T Oates proposed a method where time series data is encoded to images for visual inspection and image classification using tiled convolutional neural networks. The novel approaches of encoding images here were the GAF (Gramian Angular Field) and the MTF (Markov Transition Field). Although both encodings were used the error rates in MTF was much higher than that of GAF. Silvio Barra et al. finally used GAF proposed method to classify and forecast stock data. The proposed image encoding was then fed into CNN models for classification. The models achieved accuracies of 56.632% 46.875% and 20.00%.

III. Objective

Most of the research in market prediction and financial forecasting is based on traditional ARMA or ANN or machine learning approaches. These models are commonly trained on time series data describing a market index in the past, with the goal of predicting its future trend. The aim of this work is to achieve market prediction over the IBM stocks, by using CNNs, with the training phase executed over GAF images (particularly, the GADF).

IV. Dataset Description

The Dataset comprises of IBM stock data from 2nd January 1998 to 21st April 2022. Columns consist of Date, Time, Open Value, High, Low, Close Value, Volume of Stock. The data is recorded minute by minute on a daily basis.

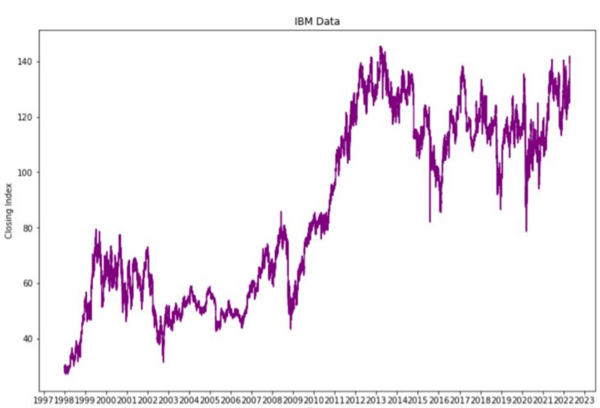

Fig. 1. Time Series Plot

V. Methodology

A. Pre - Processing

The data which we extracted need some pre-process before we use it , data also has trading activity that happened on weekends, holidays, and off trading hours so we drop unnecessary data by removing non-trading days and times.

B. Trading Strategy

Our system is designed to mimic a traditional intra-day trading strategy. This method entails buying or selling a certain financial instrument (in our case, IBM stocks) while ensuring that any open positions are closed before the market closes for the day. Specifically, we construct our strategy so that the end output of our system for each trading day is one of the following actions:

- A long action, which consists of buying the stock, and then selling it before the market closes;
- A short action, which consists of selling the stock (using the mechanism of the uncovered sale), and then buying it before the market closes;
- A hold action, which consists of deciding not to invest in that day.

The ideal goal of this technique is for the system to select the action that maximizes the economic return (i.e., profit) of the day, given a prediction about the stock price trend on that day (i.e., whether the price will rise or fall). Thus, a long action is chosen whenever our system predicts that the price will rise that day; conversely, a short action is chosen if our system predicts that the price will fall that day; and finally, a hold action is chosen whenever the system is not sufficiently sure about market behavior.

C. Gramian Angular Fields Imaging

The GAF imaging is an elegant way to encode time series as images. This has been proposed by Wang and Oates. The main reasons which led to the definition of this approach regards the possibility to use existing pre-trained models, rather than training recurrent neural networks from scratch or using 1D-CNN models. So basically Gramian Angular Fields (GAF) are images representing a time series in a non-Cartesian coordinates system (i.e. each point on the plane is referenced by a X and Y axis). Instead the coordinates are mapped by a Polar Ordinate system (i.e. each point on the plane is determined by a distance from a reference point and an angle from a reference direction). Thus each GAF represents a temporal correlation between each time point.

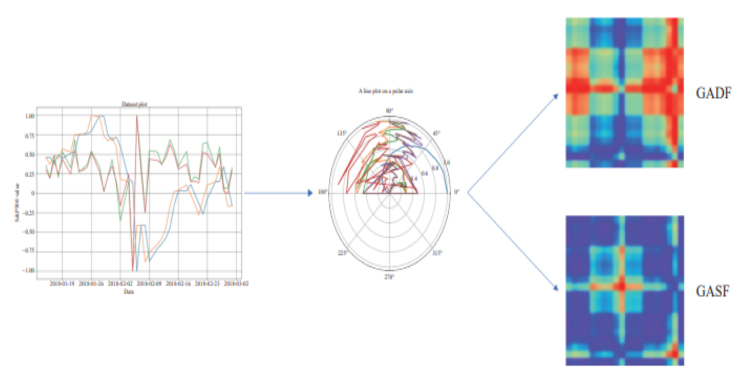

Fig. 2. Time series to GAF

Below figure shows the composition approach in which (a)–(d) are four GADF images built from four time-series

(1hr,2hr,4hr,1day) which differ for their aggregation intervals. The composition aims at building a unique image, which considers the evolution of the time series in a fixed period of time.

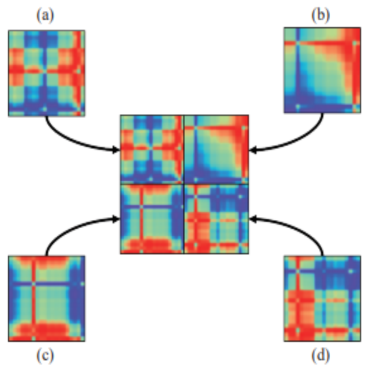

Fig. 3. GAF Quadrants

D. *Cost-Sensitive Learning and Models*

The class imbalanced datasets will occur in many real-world applications where the class distributions of data are highly imbalanced. Cost-sensitive learning is a common approach to solve this problem. In this approach, balanced class weights are calculated and passed to the model while the fitting process so that the model will penalize the prediction mistakes of minority class proportionally based on how underrepresented it is. In this work, two DCNN models are designed. The first CNN1 model has 3 convolution layers of filter size 32, 64 and 128. Each convolutional layer is immediately followed by ReLU activation and max pooling layer of pooling size 2. After the convolution layers, dropout regularization is used and the output is flattened and passed to a Dense layer which contains 128 neurons. This layer is followed by ReLU activation and dropout regularization. Finally, a dense layer of a single neuron is used with a sigmoid activation function. Architecture of the 2nd convolutional neural network involved. It consists of a simplified version of the VGG-16 network, composed by 5 convolutional layers and a fully-connected one. Although our approach is independent of the network adopted, our choice was motivated by the fact that very deep networks were not suitable for the task, given the low number of samples at our disposal (IBM stocks only has a few thousands of daily samples).

VI. Results

Model/Metric	Accuracy	Precision	Recall	F1
CNN	0.478	0.487	0.478	0.476
CS CNN	0.492	0.493	0.492	0.490
CNN1	0.453	0.456	0.453	0.451
CS CNN1	0.5	0.502	0.506	0.509

TABLE I
Results With Hold Label

Model/Metric	Accuracy	Precision	Recall	F1
CNN	0.54	0.539	0.54	0.539
CNN1	0.515	0.524	0.515	0.504

TABLE II
Results Without Hold Label

VII. Conclusion

We suggested a unique strategy for projecting market behavior in this experiment by embedding time series to GAF images and employing deep learning technologies. For a classification challenge, the generated CNNs were used to GAF pictures. The CNNs were also fed a cost-sensitive learning algorithm. The IBM stocks futures market, where we trained, verified, and tested our networks, and the overall ensemble, yielded excellent results. Thus, the GAF imaging approach has been utilized within the financial technology arena, bringing the benefits of CNN.

VIII. Future Work

Our team is now analyzing the tuning of numerous hyper parameters and will continue to do so in the future. We would also like to test our approach by converting Time Series Data into Network structures which can be fed into the CNN. We can further note any analysis changes that were made during this particular change in the time series conversion approach.

References

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