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ENERGY EFFICIENT MULTIPATH ROUTING PROTOCOL FOR MOBILE AD-HOC NETWORK USING THE FITNESS FUNCTION

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ABSTRACT

The extensive usage of time series analysis and forecasting in many real-world applications makes it critically important. The stock market is a dynamic and significant component of modern financial markets. In the last ten years, there has been a surge of interest among academics in using stock market time series data for analysis and prediction. There is a lot of interest in the question of how to label financial time series data in order to assess the efficacy of machine learning models for making predictions and, ultimately, to calculate the returns on investments. On the other hand, non-linearity and apparent short-term unpredictability characterise most financial time series data. This research proposes a novel ARIMA model that uses continuous trend labelling to forecast the behaviour of the stock market. One method for forecasting time series values is the ARIMA model, which stands for Auto Regressive Integrated Moving Average. The continuous trend aspects of financial time series data may be extracted using an automated labelling approach. When compared to state-of-the-art methods, the results demonstrate that the suggested technique produces a much lower degree of incorrect prediction.

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Introduction

The stock market is a dynamic and significant component of modern financial markets. Predicting stock prices has been a popular area of study over the last few decades due to the increasingly competitive nature of the financial industry. For a long time, time series analysis was dominated by popular stock volatility prediction methods like autoregressive and moving average [1]. Data mining methods have become more popular for stock price analysis due to the proliferation of advanced computer technologies. prediction. Improvements in prediction performance have been achieved via the development of several inductive learning-based algorithms employing previous stock price data. These approaches include neural networks and k-nearest neighbour. A big flaw with these current methods is that they ignore other data and how they affect market volatility in favour of relying only on past prices. Predictions of financial time series using machine learning techniques have grown in popularity in recent years. There is a lot of interest in the question of how to label financial time series data in order to assess the efficacy of machine learning models for making predictions and, ultimately, to calculate the returns on investments. Traditional approaches to financial time series labelling mostly use comparisons to data from a very short future period to assign labels to the present [2].
In order to make judgements based on the predicted changes in time series trends, this research offered a new way to characterise the characteristics retrieved from continuous trends. One dynamic approach to uni-variate forecasting is the ARIMA model, which may be used to predict the values of a time series in the future. Data used to train machine learning models may also be automatically labelled using an algorithm that takes a parameter as input. The outcomes of the prediction process were contrasted with those produced by the conventional approach of labelling time series data. In terms of classification accuracy, the automatically labelling algorithm outperformed the typical labelling procedure. Various investing techniques were developed and compared based on their performance. This paper's suggested strategy significantly outperformed the alternatives.

I. LITERATURE SURVEY

Because it gives people the opportunity to learn about money by financing their resources on shares and derivatives of different companies, a share market might be a location that investors are very interested in. In order to forecast the performance of the stock market, one might use one of several distinct methods. Ten million investors have been paying attention to the securities market since its inception, and it mirrors the economy's fluctuations [3]. Since the securities market is known for its terrible, high-yield characteristics, investors are engaged in securities market research and trend forecasting. Unfortunately, traditional mathematical and applied mathematics methods for predicting the securities market have not been successful due to the market's complex interplay with politics, the economy, and a host of other factors; furthermore, the market's internal laws, such as the non-linear nature of value (stock index) changes and the high noise characteristics of shared knowledge, further impede accurate forecasting. With its robustness and fault-tolerant features, neural networks can approximate complex nonlinear interactions [4]. Consequently, it's a perfect fit for studying stock knowledge. Most of the many proposed neural network models make use of the hop garden network. One of the most researched models in the field of feedback networks right now is the hop garden network, which is also the most popular. An analogous vegetative cell recognises the monolayer in the hop garden network, and it isConsider an associative network with symmetric connections that does not do learning. When compared to the time-series knowledge of stock data, such as previous prices, many external elements, such news of large acquisitions, company bankruptcies, or unforeseen political and economic uncertainty, tend to be less aligned [5]. Nonetheless, the market's time series behaviour might be significantly affected by such information sources. Multiple academics have recently delved into the topic of stock price prediction, specifically looking at how to increase forecast performance by integrating news with previous prices [6]. The majority of these studies have used data mining methods or improved upon them to investigate when and how market news could impact stock prices by influencing investor behaviour.

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On the other hand, some academics have contended that trading volume is a useful indicator of investor behaviour in the stock market. There have been several exploratory research that demonstrate how changes in stock volume affect stock price fluctuations. The efficacy of integrating trading volume with historical prices in predicting stock volatility has been the subject of additional research [7–10]. To our knowledge, no prior research has investigated the possibility that stock market volatility prediction could benefit from additional and stronger indicators provided by correlations of price changes over time, trading volumes, and news (both positive and negative).

II. PROPOSED SYSTEM

The Block diagram of the proposed model is shown in figure (1).

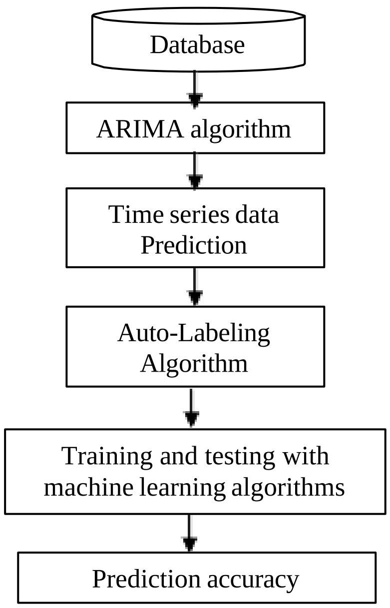

Fig. 1: BLOCK DIAGRAM OF PROPOSED SYSTEM

In the statistical analysis of time series, autoregressive integrated with moving- average (ARIMA) models provide a parsimonious description of a (weakly) stationary stochastic process in terms of two polynomials the auto-regression the moving average.

Autoregressive model: The notation AR(p) refers to the autoregressive model of order p. The AR(p) model is written as,

3.1. ARIMA Algorithm

1 Review: Time series modelling and forecasting

Required to estimate the parameters of an ARMA (p,q) model.

Let assume (for now) that:

1. The model order (p and q) is known, and
2. The data has zero mean.

If (2) is not a reasonable assumption, we can subtract the sample mean y bar, fit a zero- mean ARMA model, φ(B)Xt= θ(B)Wt, to the mean-corrected time series Xt= Yt− y bar, and then use Xt+ y bar as the model for Yt.

2. Parameter estimation

Assume that {Xt} is Gaussian, that is, φ(B)Xt= θ(B)Wt, where Wt is the Gaussian.

Choose φi, θjto maximize the *likelihood*: L(φ, θ, σ2) = fφ,θ,σ2(X1, . . . , Xn),

where fφ,θ,σ2 is the joint (Gaussian) density for the given ARMA model.(c.f. choosing the parameters that maximize the probability of the data.)

3. Maximum likelihood estimator

Suppose that $X_1, X_2, X_3, \cdots, X_N$ is drawn from a zero mean

Gaussian ARMA (p,q) process. The likelihood of parameters φ ∈ Rp, θ ∈ Rq, σ2w ∈ R+ is defined as the density of

$$X = c + \sum$$

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φ X + ϵ--(1)

$X = X_1, X_2, X_3, \cdots, X_N$ under the Gaussian

t $i=1$ i $-i$ t

Where, φ are parameters, is a constant, and the c random variable Et is white noise. Some constraints are necessary on the values of the parameters so that the model remains stationary

Moving-average model: The notation MA (q) refers to the moving average model of order q:

$$X_t = \mu + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \text{---(2)}$$

Where, the $\theta_1, \ldots, \theta q$ are the parameters of the model, μ is the expectation of (often assumed to equal 0), and the ε_t are white noise error terms.model with those parameters:

L(φ, θ, σw2) = 1 (2π)n/2 |Γn|1/2 exp−1 2X′Γ− n 1X,

where |A| denotes the determinant of a matrix A, and Γnis the variance/covariance matrix of X with the given parameter values. Themaximum likelihood estimator (MLE) of φ, θ, σw2 maximizes this quantity.

3.2 Automatic Labeling Method

To better conform to the law of averages, it is theoretically possible to identify the market's continuous up and down trends and use a machine learning model to forecast the market's trend direction while disregarding the typical variations. management of the financial markets. After the parameter τ is input, the labelling processes provide the label vector set y. The method of identifying past data is also distinct since many investors' assessments of the ongoing trend vary, even within the same commodity or stock market. The rationale behind this is that various investment strategies and approaches are prompted by many variables, such as varying levels of money, risk tolerance, investment decision-making cycles, and so on. The ongoing trend of the market is therefore defined differently by many investors. Consequently, investors may train models to find the best fit for guiding their investments by labelling historical data with unique parameters. The authors of this work offered a method for automated labelling. The market is said to be in a rising segment when it goes over a certain percentage parameter τ from its current low point or in a falling segment when it goes below that same proportion parameter from its current high point. For the labelling procedure, the percentage threshold parameter τ must be provided in order for the outcome to be distinct. According to the study presented in the article, the value of τ was 0.15. method employing Computation Tree Logic (CTL) presents the method for the automated labelling process that is dependent on a specified parameter τ.

Auto-Labeling Data for CTL

Input: Original Time series data $X = [x_1, x_2, x_3, \cdots, x_N]^T, \omega > 0$, which represents HT=$t_1$, used to mark the time when the highest price occurs; $x_L = x_1$, used to mark the lowest price; LT=t_1, used to mark the time when the lowest price occurs; Cid=0, used to mark the current direction of labeling; FP_N =0, the index of the highest or lowest point obtained initially.

for i = 1:N
  if (xi > FP + x1*!)
    Set
    $[x_H, HT, FP\_N, Cid] = [x_i, t_i, i, -1]$
    and end for
  if (xi < FP- x1*!)
    Set
    $[x_L, LT, FP\_N, Cid] = [x_i, t_i, i, -1]$
    and end for
end for i

for i = FP_N+1:N

if (Cid > 0)

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if $(x_i > x_H)$
Set $[x_H, HT] = [x_i, t\ ]$
if $(x_i < x_H - x_H{}^*\omega$ and LT<=HT)
for j = 1:N
if $(t_j >$ LT and t_j<=HT)
Set $t_j = 1$
end for j

Set

$[x_L, LT, Cid] = [x_i, t_i, i, -1]$

if (Cid < 0)

if $(x_i < x_L)$
Set $[x_L$, LT] = $[x_i, t\ ]$
if $(x_i > x_L + x_L{}^*\omega$ and HT<=LT
for j = 1:N
if $(t_j >$ HT and $t_j <=$ LT)
Set $y_i = -1$

end for j

Set $[x_H, HT, Cid] = [x_i, t_i, 1]$

the proportion threshold parameter of the trend definition
Output: The label vector
$X = [label_1, label_2, label_3, \cdots, label_N]^T$

end for i

RESULTS

Initialization of related variables:

FP=x_1, which represents the first price obtained by the algorithm; $x_H = x_1$, used to mark the highest price;The proposed model trained with different models on the stock price of a single company from NSE (National Stock Exchange) of and Bombay Stock Exchange (BSE) predicted for a HCL company. The

network was able to predict for BSE even though it was trained with NSE data. This was possible because both the stock markets share some common inner dynamics.

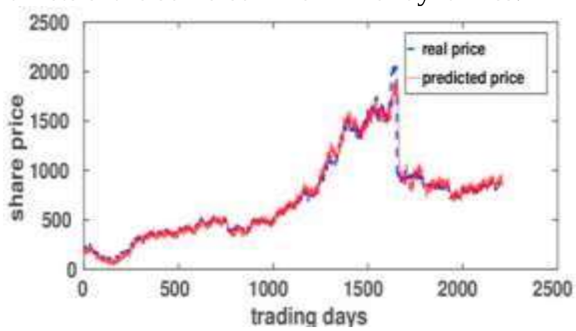

Fig 3: PREDICTION OF REAL AND PREDICTED PRICES

The prediction and real prices of HCL company for the time period of 2009 to 2019 are obtained by using the proposed model. It was almost successful in identifying the pattern of real price by the predicted prices as shown in figure (3) by capturing the change in system between the period 1400 and 1800 days.

III. CONCLUSION

This research proposes using the ARIMA model with the auto labelling approach for time series prediction in order to forecast the direction of the stock market. To forecast the values, the system compiles past data. You may trust the stock's true worth that this document provides. In order to extract the continuous trend characteristic from financial time series data, this research suggested a new data labelling approach called CTL. This study introduced a novel ARIMA algorithm for use during the feature preprocessing step. Afterwards, two deep learning models and four supervised machine learning techniques were used to forecast financial time series using the

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continuous trend characteristics collected from financial time series data using an automated labelling approach. Two stock indices and three equities were used in the studies to prove that CTL outperformed the state-of-the-art data. classification accuracy as well as other measures used to evaluate the labelling procedure.

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