HYBRID INFORMATION MIXING MODULE FOR STOCK MOVEMENT PREDICTION

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Abstract:

With the continuing active research on deep learning, research on stock price prediction using deep learning has been actively conducted in the financial industry. This paper proposes a method for predicting stock price movement using stock and news data. The stock market is affected by many variables; thus, market volatility should be considered for predicting stock price movement. Because stock markets are efficient, all kinds of information are quickly reflected in stock prices. We create a new fusion mix by combining price and text data features and propose a hybrid information mixing module designed using two map blocks for effective interaction between the two features. We extract the multimodal interaction between the time-series features of the price data and the semantic features of the text data. In this paper, a multilayer perceptron-based model, the hybrid information mixing module, is applied to the stock price movement prediction to conduct a price fluctuation prediction experiment in a stock market with high volatility. In addition, the accuracy, Matthews correlation coefficient (MCC) and F1 score for the stock price movement prediction were used to verify the performance of the hybrid information mixing module.

Keywords: *stock movement prediction, deep learning, stock price, Matthews correlation coefficient, multi layer perceptron, multimodal, Long Short TermMemory(LSTM),Gated Recurrent Unit (GRU), Perceptron Based Model*

1. INTRODUCTION

The With the continuing deep learning research, deep learning technology has been introduced in the financial industry. As stock market volatility has expanded during the COVID-19 pandemic, the accuracy of stock price movement prediction has become a significant challenge for effective stock market forecasting research. The importance of studies on stock price prediction is increasing in natural language processing (NLP) and the financial industry. The stock market is a highly volatile market affected by company-related information and stock price indicators; thus, research on predicting stock price movement using various variables is constantly being conducted. First, time-series-based stock price movement prediction research has been conducted in two primary studies: one using stock price data and one using text data, such as stock-related news and Twitter. Research using stock price data generally predicts stock price movement by converting the opening, high, low, and closing prices and the trading volume into technical indicators. Methods for learning time-series characteristics using the convolutional neural network (CNN) or recurrent neural network (RNN) have been proposed to predict the variability of time-series data. However, technical analyses using stock price data face a limitation in that they cannot reveal patterns that affect stock price fluctuations. In addition to price and text data, the relationship between companies affects stock market volatility. By establishing an attention mechanism-based model and analyzing the influence on stocks using price, text, and company relationship data, stock price movement prediction studies have also been conducted. Because various types of information affect stock prices, a study is conducted to predict stock price movement by analyzing the relationship between financial data, social media, and stocks in a hierarchical fashion based on the hierarchical graph attention network. We propose a new method to predict stock price movement. In this paper, we analyze market signals for stock market volatility using price data and text data. The patterns of stock market volatility are identified by analyzing stock data using RNN-based models: long short-term memory (LSTM) and gated recurrent units (GRU). In addition, to reflect the stock market information contained in the text data for stock price movement prediction, the contextual information is identified through the contextual word embedding of the bidirectional encoder representations from transformers (BERT). The multimodal time-series market signals from the price and text data affect the stocks. After extracting the time-series features of the price data and sematic features of the text data, the extracted features are combined to create a mixed feature containing multimodal information. The interaction between the features of the price and text data is strengthened by mixing the characteristics of the mixed feature via the hybrid information mixing module. We devise a hybrid information mixing module consisting of two multilayer perceptron (MLP) blocks to improve the performance of stock price movement prediction by effectively mixing the information for two features. The hybrid information mixing module consists of the feature-mixing MLP and interaction-mixing MLP

2. LITERATURESURVEY

[1] "Stock movement prediction from tweets and historical prices"

Predicting stock market is vital for investors and policymakers, acting as a barometer of the economic health. We leverage social media data, a potent source of public sentiment, in tandem with macroeconomic indicators as government-compiled statistics, to refine stock market predictions. However, prior research using tweet data for stock market prediction faces three challenges. First, the quality of tweets varies widely. While many are filled with noise and irrelevant details, only a few genuinely mirror the actual market scenario. Second, solely focusing on the historical data of a particular stock without considering its sector can lead to oversight. Stocks within the same industry often exhibit correlated price behaviors. Lastly, simply forecasting the direction of price movement without assessing its magnitude is of limited value, as the extent of the rise or fall truly determines profitability. In this paper, diverging from the conventional methods, we pioneer an ECON. The framework has following advantages: First, ECON has an adept tweets filter that efficiently extracts and decodes the vast array of tweet data. Second, ECON discerns multi-level relationships among stocks, sectors, and macroeconomic factors through a self-aware mechanism in semantic space. Third, ECON offers enhanced accuracy in predicting substantial stock price fluctuations by capitalizing on stock price movement. We showcase the state-of-the-art performance of our proposed model using a dataset, specifically curated by us, for predicting stock market movements and volatility.

[2] "Hybrid neural networks for learning the trend in time series,"

Trend of time series characterizes the intermediate upward and downward behaviour of time series. Learning and forecasting the trend in time series data play an important role in many realapplications, ranging from resource allocation in data centers, load schedule in smart grid, and so on. Inspired by the recent successes of neural networks, in this paper we propose TreNet, a novel end-toned hybrid neural network to learn local and global contextual features for predicting the trend of time series. TreNet leverages convolutional neural networks (CNNs) to extract salient features from local raw data of time series. Meanwhile, considering the long-range dependency existing in the sequence of historical trends, TreNet uses a long-short term memory recurrent neural network (LSTM) to capture such dependency. Then, a feature fusion layer is to learn joint representation for predicting the trend. TreNet demonstrates its effectiveness by outperforming CNN, LSTM, the cascade of CNN and LSTM, Hidden Markov Model based method and various kernel based baselines on real datasets.

[3] "Stock prediction using combination of BERT sentiment analysis and macro economy index,"

This paper proposes a stock price prediction model, which extracts features from time series data and social networks for prediction of stock prices and evaluates its performance. In this research, we use the features such as numerical dynamics (frequency) of news and comments, overall sentiment analysis of news and comments, as well as technical analysis of historic price and volume. We model the stock price movements as a function of these input features and solve it as a regression problem in a Multiple Kernel Learning regression framework. Experimental results show that our proposed method outperforms other baseline methods in terms of magnitude prediction measures such as RMSE, MAE and MAPE for three famous Japan companies' stocks in US stock market. The results indicate that features other than mining from stock prices themselves improved the performance.

[4] ''DP-LSTM: Differential privacy-inspired LSTM for stock prediction using financial news,''

Stock price prediction is important for value investments in the stock market. In particular, short-term prediction that exploits financial news articles is promising in recent years. In this paper, we propose a novel deep neural network DP-LSTM for stock price prediction, which incorporates the news articles as hidden information and integrates difference news sources through the differential privacy mechanism. First, based on the autoregressive moving average model (ARMA), a sentiment-ARMA is formulated by taking into consideration the information of financial news articles in the model. Then, an LSTM-based deep neural network is designed, which consists of three components: LSTM, VADER model and differential privacy (DP) mechanism. The proposed DP-LSTM scheme can reduce prediction errors and increase the robustness. Extensive experiments on S&P 500 stocks show that (i) the proposed DP-LSTM achieves 0.32% improvement in mean MPA of prediction result, and (ii) for the prediction of the market index S&P 500, we achieve up to 65.79% improvement in MSE.

[5] ''Stock price prediction using BERT and GAN,''

The stock market has been a popular topic of interest in the recent past. The growth in the inflation rate has compelled people to invest in the stock and commodity markets and other areas rather than saving. Further, the ability of Deep Learning models to make predictions on the time series data has been proven time and again. Technical analysis on the stock market with the help of technical indicators has been the most common practice among traders and investors. One more aspect is the sentiment analysis - the emotion of the investors that shows the willingness to invest. A variety of techniques have been used by people around the globe involving basic Machine Learning and Neural Networks. Ranging from the basic linear regression to the advanced neural networks people have experimented with all possible techniques to predict the stock market. It's evident from recent events how news and headlines affect the stock markets and crypto currencies.

[6] ''Deep attentive learning for stock movement prediction from social media text and company correlations,''

In the financial domain, risk modelling and profit generation heavily rely on the sophisticated and intricate stock movement prediction task. Stock forecasting is complex, given the stochastic dynamics and non-stationary behaviour of the market. Stock movements are influenced by varied factors beyond the conventionally studied historical prices, such as social media and correlations among stocks. The rising ubiquity of online content and knowledge mandates an exploration of models that factor in such multimodal signals for accurate stock forecasting. We introduce an architecture that achieves a potent blend of chaotic temporal signals from financial data, social media, and inter-stock relationships via a graph neural network in a hierarchical temporal fashion. Through experiments on real-world S&P 500 index data and English tweets, we show the practical applicability of our model as a tool for investment decision making and trading.

PROPOSEDMETHODOLOGY

In propose work author using BERT model to extract semantic features from stock tweets and then extracting time series stock prices from stock dataset and then both features will be merge and then train by combining two different models called GRU and LSTM. LSTM will be used to train stock prices and GRU will be used to train on BERT features and then both models will be used to combine features and then trained with MLP (multilayer perceptron) to predict binary classification label as 'Stock price will go up or down'.

Advantages:

1.High Accuracy

.2.Less Time Taking

3. EXPERIMENTALANALYSIS

Importing required python classes and packages and reading, displayingmealsanditssalesdataset.Readinganddisplaying dataset of different centers which are handling sales and now we will merge both datasets to find sales from different Centers.

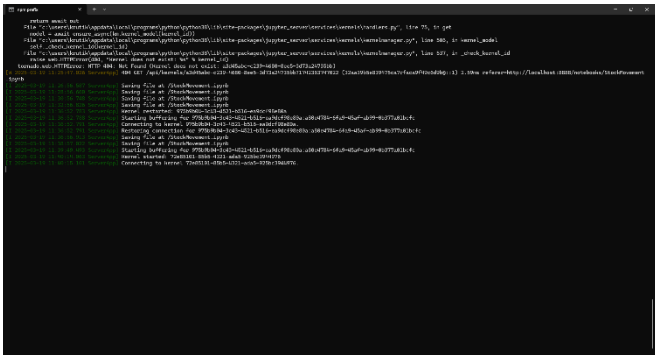


Figure 1: Running Python Server

In above screen python server is started and now open browser and enter URL as http://127.0.0.1:8000/index.html and press enter key to get below page.

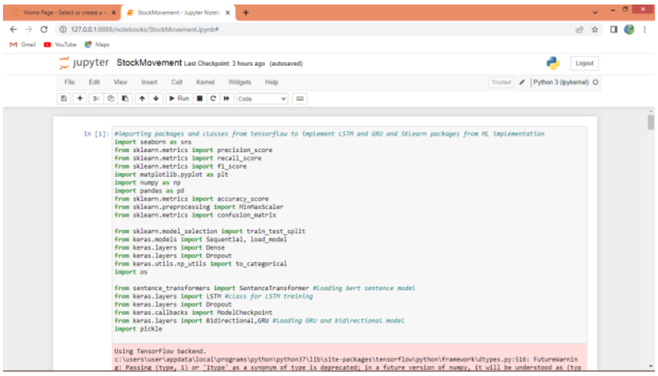


Figure2 importing required packages and classes

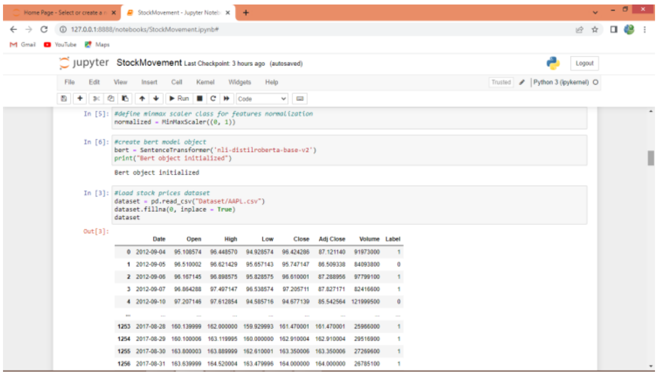


Figure 3 defining BERT model

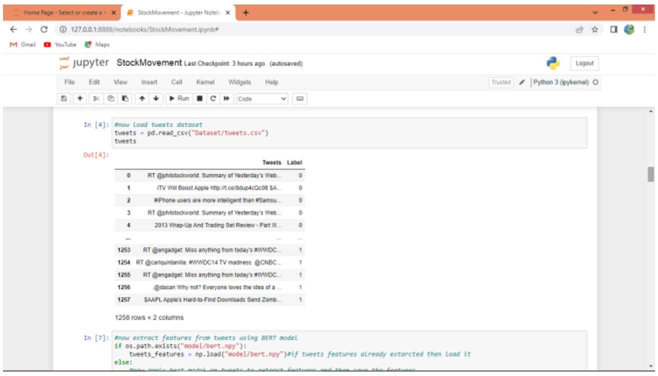


Figure 4 Reading and displaying tweets dataset

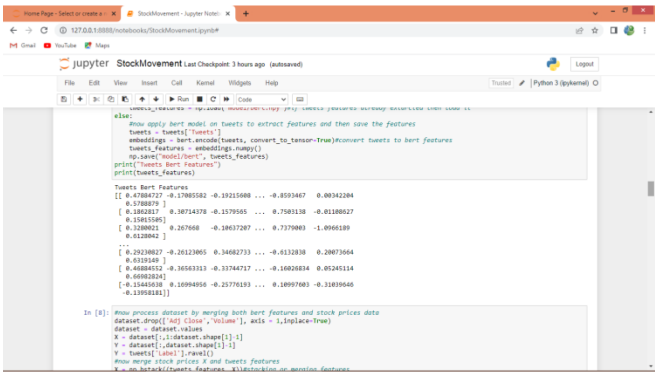


Figure5 : Applying BERT model to convert tweets into BERT features and then displaying BERT features values

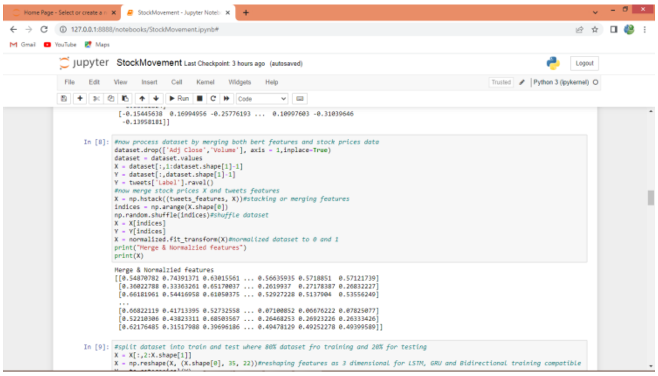


Fig6: Applying features processing such as normalization and shuffling and then displaying normalized features values

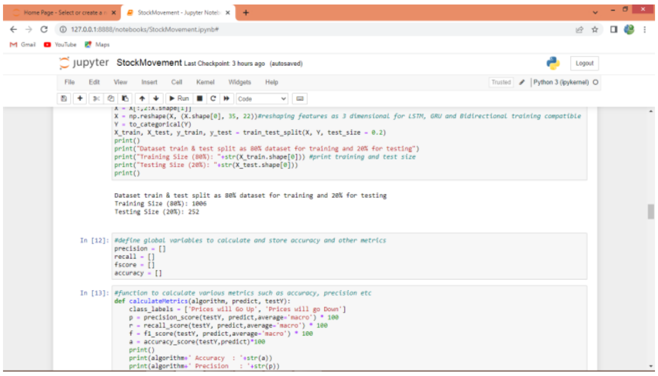


Figure7: In above screen splitting dataset into train and test and then defining function to calculate accuracy, precision and other metrics

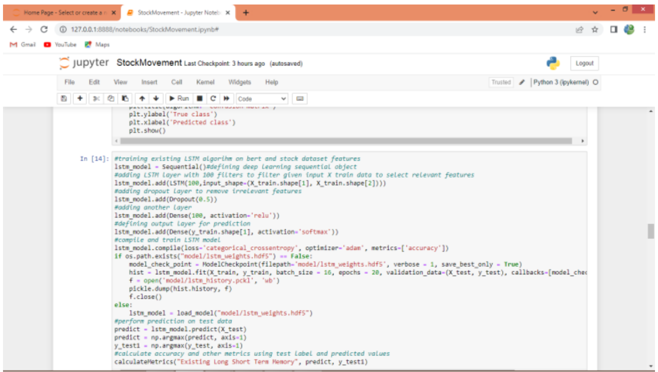


Figure8:In above screen training existing LSTM model on stock prices and BERT features and after executing above block will get below output

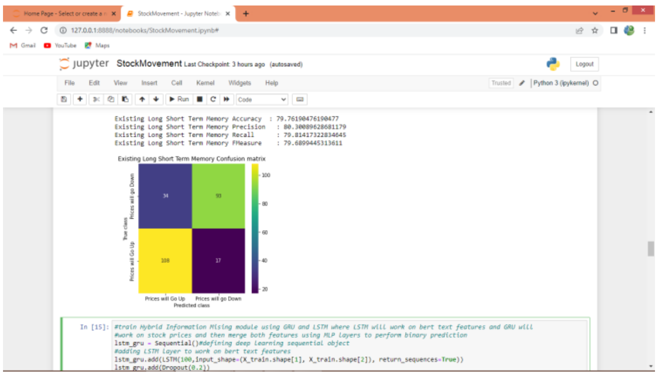
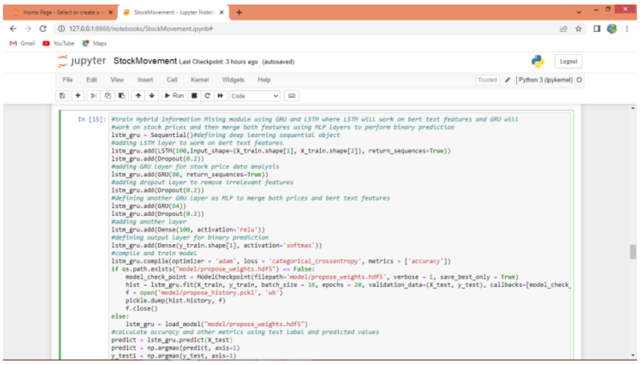


Figure9:Existing LSTM model got 79% accurac



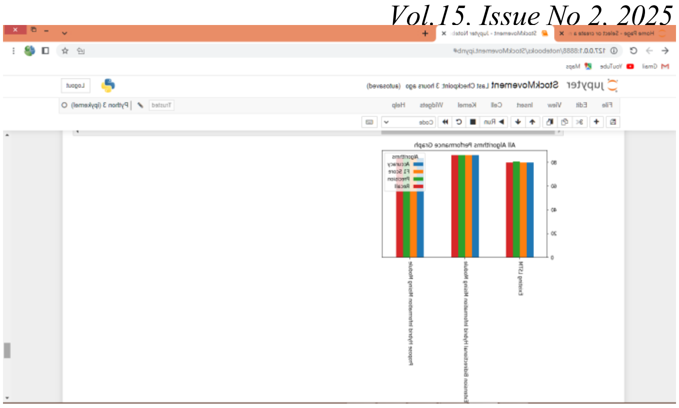
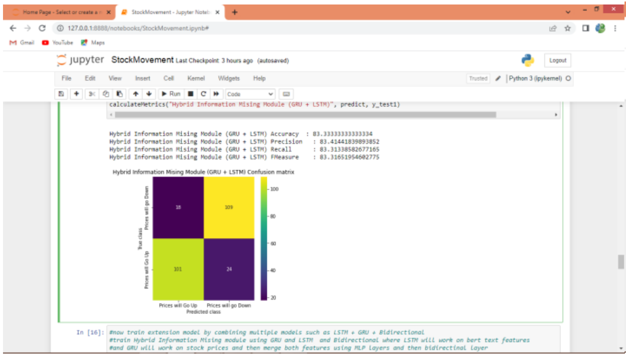


Figure10 :Training propose HYBRID model by combining LSTM and GRU layers and after executing above block will get below output

Figure14: Comparision graph of x-axis and y-axis



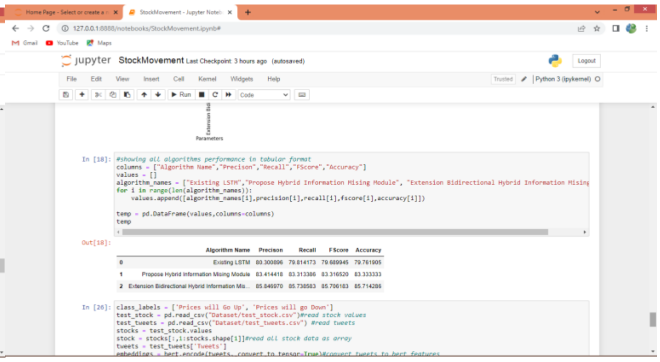
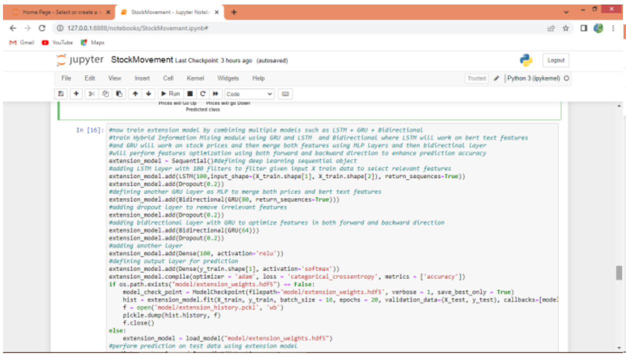


Figure 11: propose hybrid model got 83% accuracy

Figure15: Displaying all algorithms performance



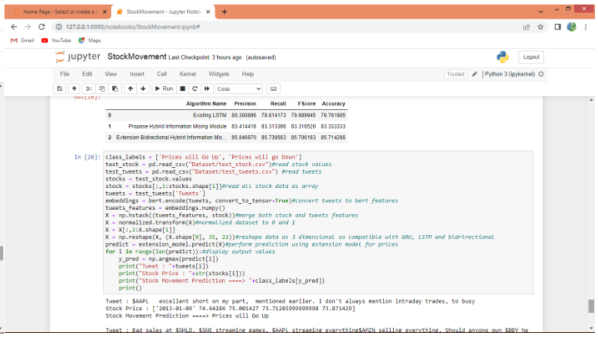
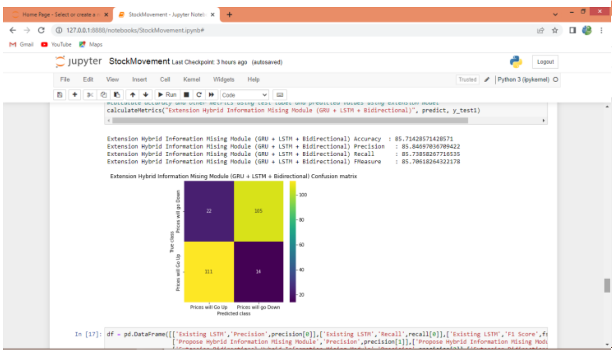


Figure 12:Training extension model by combining LSTM + GRU + Bidirectional algorithms

Figure 16: test code to read tweets and stock price



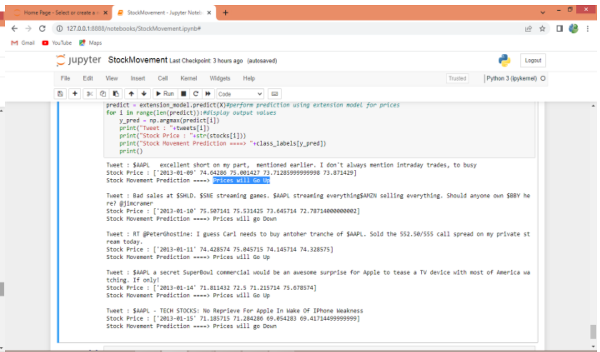


Figure 17: Predicting Stock Price

Figure 13: Extension got 85% accuracy

4.CONCLUSION

In this paper, we focus on the stock price movement prediction. After extracting time-series and semantic features, we proposed creating a mixed feature by mixing two characteristics in a hybrid information mixing module and mixing the multimodal information in the mixed feature. The featuremixing and interaction-mixing MLPs of the hybrid information mixing module operate independently in a row-wise and column-wise manner. This learning process strengthens the interaction between the two data characteristics in the row and column information in the mixed feature to predict stock price movement. The proposed hybrid information mixing module predicts stock price movements better than the other models. The experiment results confirm that the accuracy, MCC, and F1 score of the hybrid information mixing module are 69.20%, 0.43, and 76.17%, which is improved compared to the previous model, exhibiting high performance.

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