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Stock Analysis – Analysis Of stock market

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ABSTRACT: Our project is the recent trend in stock market predictions technologies is the use of machinelearning which Makes predictions based on the values of current stock Market indices by training on theirpreviousvalues.Machinelearningitselfemploysd ifferentmodelstoMakepredictioneasierandauthentic . The Technical and fundamental or the time series analysis is used By the most of the stockbrokers whilemaking the stock Predictions. The programming language is used to predict the Stock market usingmachine learning is Python. Each machine learning algorithm is tested against the National Association ofSecurities Dealers Automated Quotations System (NASDAQ), New York Stock Exchange (NYSE),Nikkei, and Financial Times Stock Exchange (FTSE). Furthermore, several machine learning algorithmsare compared with a normal and a leaked data set. In this project we are using Machine learning algorithmcalledSupportVectorMachine(SVM)algor ithm,whichgiveapredictionofvariousaspectsofaparti cular stock or an index, such as future values of the opening price, closing price, index value etc. Thiswillhelpinvestorsandtradersmakebetterandfaste rdecisions

Keywords:openingprice,Forecasting,CloseStockM arket,SVM.

Introduction: This project aims to build a application that provides traders to trade well. Thisapplicationwillusethemachinelearningalgorith mcalledSupportvectormachine(svm)whereuserscan easily trade and perform trading activities. One of the key features of this Application is trades getnotifications updates. In this notifications play a much more crucial role since they help users keep trackoftheirorders.Overallthisprojectwillprovideaov erallvaluabletoolforanyonewhoneedstotrade. Mostlyforbeginnerstotradesafelyandforexperienced peopletooitmakesmorecomfortabletrading.

I. LITERATUREREVIEW

The literature review identifies the strengths and limitations of SVM about the stock market analysis.
Asstockmarketcomesunderthesecondarymarket,sec uritiesarebuyersandsellersamonginvestors.
Secondary market deals with excellent securities. This market is made of organized exchanges and it hastrading floor, where orders are transmitted for exchange. All the trading of stocks is maintained andguided by the exchanges. The rules and regulations are set down by the exchanges. For investors, indicesgive the direction of the entire market. They use indices to track the performance of the stock market. ifpossible, a change in the price of an index represents an exactly proportional change in the stocksincluded in the index. The ASPI is one of the principal stock indices of the CSE and it measures themovementofsharepricesofalllistedcompaniesbas ed onmarketcapitalization.

Overviewofstockmarket

The stock market is a centralized marketplace where individuals and institutions can buy and sell sharesofpubliclytradedcompanies.Itprovidesaplatfo rmforinvestorstotradestocks,bonds,derivatives,ando ther financial instruments. The stock market plays a crucial role in the economy by facilitating theallocationofcapitalandenablingcompaniestoraise fundsforexpansionandgrowth.

Fundamental and Technical Analysis: Investors use different approaches to evaluate stocks.Fundamental analysis involves analyzing a company's financial health, including its earnings, revenue,balance sheet, management, and competitive position, to determine its intrinsic value. Technical analysis,on the other hand, focuses on historical price and volume patterns, using charts and indicators to forecastfuture price movements. Investing in the stock market involves

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risk. Prices can fluctuate, and investorsmay experience losses. However, historically, the stock market has provided higher average returnscompared to other asset classes over the long term. The risk and potential return of stocks vary based onfactorssuchascompanyperformance,marketconditions,andtheinvestor'srisktolerance.
Overviewofsupportvectormachine
Support Vector Machine (SVM) is a supervised machine learning algorithm used for classification andregression tasks. It analyzes data and builds a model that can be used to predict the category or value ofnew, unseen instances. SVMs are known for their ability to handle complex datasets and achieve highaccuracy.HerearesomekeyaspectsofSVMs:
Given a set of training input, SVM is to find an optimal hyperplane that separates different classes in adataset. SVM will attempt to separate the data instances into two categories with a p-1-dimensionalhyperplane, where p is the size of each data instance. SVM aims to find the hyperplane that maximizesthismargin,resultinginbettergeneralizationandimprovedperformanceonunseendata.

HowSVMWorks.
SVM requires labeled training data, where each data point is assigned a class label. The data should bepreprocessed and transformed into a suitable format, typically numerical values. SVM operates in a high-dimensional feature space, so it's essential to select or engineer appropriate features that capture theunderlyingpatternsinthedata.Thisstepcansignificantlyimpacttheperformanceof SVMInthetrainingphase,SVMfindstheoptimalhyperplanethatmaximallyseparatestheclasses.Thealgorithmaimstofind a hyperplane that not only separates the data but also maximizes the margin, which is the distancebetween the hyperplane and the nearest data points of each class. This margin is crucial as it helps theSVM generalize well to unseen data. Once the SVM is trained, it can be used to make predictions on new,unseen data points. The algorithm maps the new data points into the same feature space using the chosenkernel function. It then determines which side of the hyperplane the new data point falls on, assigning it tothecorrespondingclasslabel.

II. PROBLEMSTATEMENT

To develop a reliable and accurate model for stock market prediction, using historical financial data andother relevant factors. The goal is to predict future stock prices or trends, enabling investors and traders tomakeinformeddecisionsandoptimizetheirportfolio strategies.

III. REQUIREDTOOLS

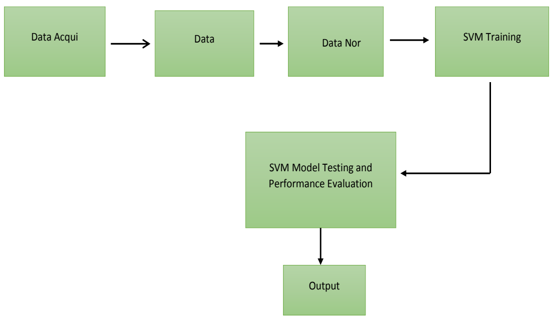
1. **Python**
2. **Datasets–**previousdatasetfilesofstockmarket

3. **Keras:**itisanopen-sourcedeeplearningframeworkwritteninPython. Itisdesignedtosimplifythe process of building and training deep neural networks by providing a high-level API thatabstractsawaymanyofthelow-leveldetailsofbuildinganeuralnetwork.

4. **Scikit-learn:it**isapopularopen-sourcemachinelearninglibraryforPython.Itisdesignedtoprovidesimpleandefficienttoolsfordataanalysisandpredictivemodeling.

IV. METHODOLOGY

TheModelArchitecture
The architecture of the SVM model for stock closing price prediction is shown below. The description ofeachblockinthearchitecturehowitrelatestootherblockisprovidedinthesubsequentsections.



S2R

DataAcquisitionandDescription
The data used for training and testing of the model was collected from NSE-TATAGLOBAL data. It iscomprised of the opening price, high price, low price, closing price, volume and adjacent close of eachtradingday

Dataselection
The data selected from the acquired data and making a total of 170 trading days. The selected data wasdividedinto70%fortrainingand30%fortesting.Table1showsasampleofthedataused

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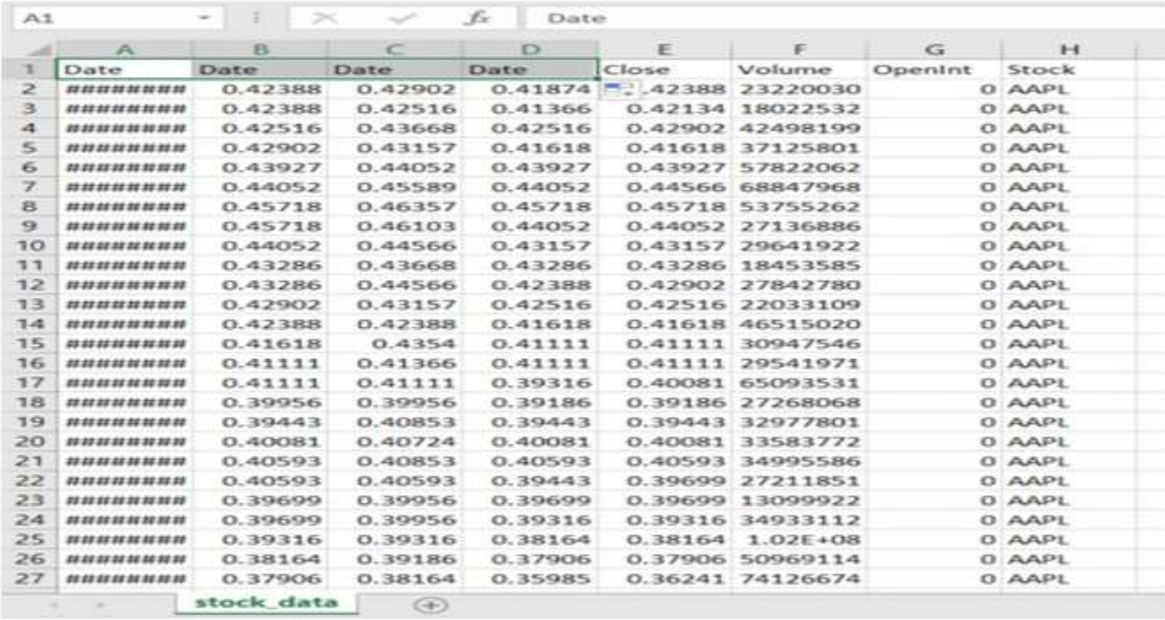


	A	B	C	D	E	F	G	H
1	Date	Date	Date	Date	Close	Volume	OpenInt	Stock
2	#########	0.42388	0.42902	0.41874	.42388	23220030	0	AAPL
3	#########	0.42388	0.42516	0.41366	0.42134	18022532	0	AAPL
4	#########	0.42516	0.43668	0.42516	0.42902	42498199	0	AAPL
5	#########	0.42902	0.43157	0.41618	0.41618	37125801	0	AAPL
6	#########	0.43927	0.44052	0.43927	0.43927	57822062	0	AAPL
7	#########	0.44052	0.45589	0.44052	0.44566	68847968	0	AAPL
8	#########	0.45718	0.46357	0.45718	0.45718	53755262	0	AAPL
9	#########	0.45718	0.46103	0.44052	0.44052	27136886	0	AAPL
10	#########	0.44052	0.44566	0.43157	0.43157	29641922	0	AAPL
11	#########	0.43286	0.43668	0.43286	0.43286	18453585	0	AAPL
12	#########	0.43286	0.44566	0.42388	0.42902	27842780	0	AAPL
13	#########	0.42902	0.43157	0.42516	0.42516	22033109	0	AAPL
14	#########	0.42388	0.42388	0.41618	0.41618	46515020	0	AAPL
15	#########	0.41618	0.4354	0.41111	0.41111	30947546	0	AAPL
16	#########	0.41111	0.41366	0.41111	0.41111	29541971	0	AAPL
17	#########	0.41111	0.41111	0.39316	0.40081	65093531	0	AAPL
18	#########	0.39956	0.39956	0.39186	0.39186	27268068	0	AAPL
19	#########	0.39443	0.40853	0.39443	0.39443	32977801	0	AAPL
20	#########	0.40081	0.40724	0.40081	0.40081	33583772	0	AAPL
21	#########	0.40593	0.40853	0.40593	0.40593	34995586	0	AAPL
22	#########	0.40593	0.40593	0.39443	0.39699	27211851	0	AAPL
23	#########	0.39699	0.39956	0.39699	0.39699	13099922	0	AAPL
24	#########	0.39699	0.39956	0.39316	0.39316	34933112	0	AAPL
25	#########	0.39316	0.39316	0.38164	0.38164	1.02E+08	0	AAPL
26	#########	0.38164	0.39186	0.37906	0.37906	50969114	0	AAPL
27	#########	0.37906	0.38164	0.35985	0.36241	74126674	0	AAPL

stock_data

DataNormalization

Due to the inconsistency in the used data and to avoid the classifier from been biased towards largervalues, the selected data were normalized to the range of 0 and 1. This was done to improve theperformanceofthemodelsduringtesting.

ModelTraining

Theselectedperiodfromthedatawasdividedintotrainingandtestingdata,withtrainingdatataking70% (119 trading days) of the selected data. The SVM model was trained using the opening, high andlowpricesasinputstopredicttheclosingpriceastarget.

ModelTesting

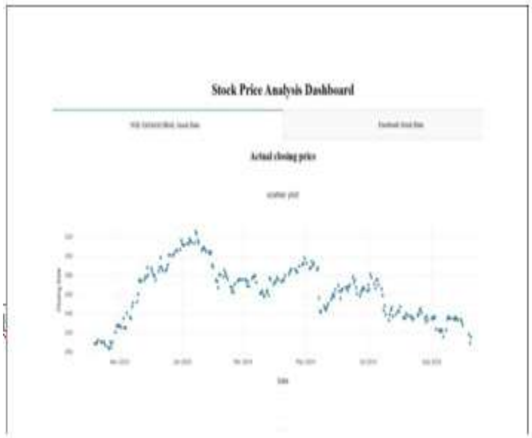
After training, each model was saved and tested externally with the 30% (51 trading days) of selecteddatatoascertain

itsperformance.Theperformanceofeachmodelwasrecordedandanalyzed.

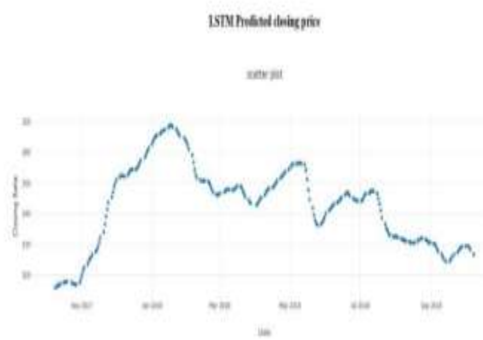
ModelPerformanceEvaluation

ThemodelwasevaluatedusingMeanAbsolutePercentageError(MAPE)andRootMeanSquaredError(RMSE).Thetwoequationsdeterminetheerrorresultingfrom thepredictionbythe proposedmodel.

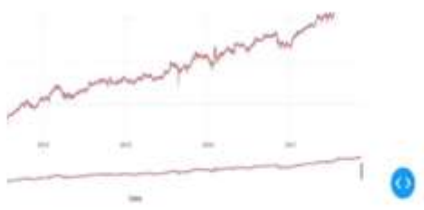
ExperimentalResults:



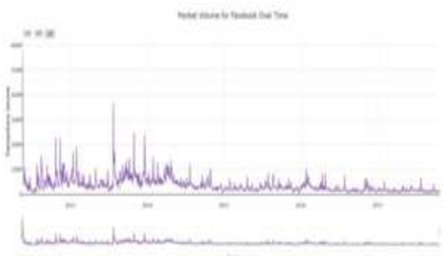
TheabovegraphistheScatterplotthatreadsstockdatafromtwoCSVfiles,oneforNSE-TATAGLOBALstockdataandanotherforFacebookstockdataandpredictstheactualclosingpriceofboththedata.



TheabovegraphistheNSE-TATAGLOBALdataisusedtotrainanLSTMmodelth atpredictstheclosingpriceofstock.



TheabovegraphistheFacebookdataofHighvsLowpriceOverTime



TheabovegraphismarketVolumeforFacebookdataOverTime

V. CONCLUSION

The stock analysis with smart notifications is and user-friendly tool that enhance user interest to tradeand to stay informed up-to-date about market conditions, market news, price charges, and any otherannouncements that may impact their trading decisions. With it advanced algorithm and machine learning techniques ,the application provides a easy to use platform for traders. Whether you area professional or beginner you can easily trade and minimize your losses, and capitalize on profitable opportunities. Overall, SVMs can be a valuable tool in stock market analysis, but their effectiveness willdependonthespecificproblemandthequalityofthedataused.Itisimportanttocarefullyevaluatetheperformanceofan SVMmodelbeforemakinginvestment decisionsbasedonitspredictions.

VI. FUTURE ENHANCEMENT:

Incorporation of more data sources: SVM models can be improved by incorporating additional datasources into the analysis. For example, social media sentiment analysis or news articles related to thestockmarketcouldbeincludedtoprovideadditional insightintothemarketmovements.

Integration of feature selection techniques: SVM models can be improved by incorporating featureselection techniques, such as principal component analysis (PCA) or feature importance ranking. Thiswould help to identify the most important features that impact the stock market and improve theaccuracyofthemodel.

Implementation of ensemble learning: SVM models can be improved by implementing ensemblelearning techniques, such as bagging or boosting. This involves training multiple SVM models andcombining their outputs to generate a more accurate prediction. Development of a real-time tradingsystem: SVM models can be implemented in a real-time trading system to provide traders with insightson potential trades. This system could be integrated with a trading platform to execute tradesautomaticallybasedontheSVMmodel'spredictions.

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