RESEARCH ARTICLE OPEN ACCESS

A Different Look At Stock Trading With LeNet5 And Particle Swarm Optimizaton (PSO)

Ahmet Bedirhan SAGIR
Istanbul Aydin University
ComputerSciences
Istanbul, TURKEY

Dr. Öğr. Üyesi Sina APAK
Istanbul Aydin University
ElectricalandElectronic Sciences
Istanbul, TURKEY

ABSTRACT
Theprimaryobjective of Stock Market Predictionalgorithms is toforecastthefuture trend of individualcompanies' financialstocks. Machine Learning andDeep Learning technologieshavebecome a new trend forstockpredictiontechnologiesthatmakepredictionsbased on historicaltrading data. Machine Learning employsvariousmodelstomakepredictionsmoreaccurateandstraightforward. Inthisarticle, weuse Machine Learning techniquestoanalyzethestockpriceover time, determinetheaveragedailyreturn, identifythelowestandhighestvalues, andultimatelypredictthefuturebehavior of thestock. Inthisstudy, weattempttocreate an automatic buy/selldecisionusing LeNet-5-based ConvolutionalNeural Networks (CNN) andParticleSwarm Optimization in stocktrading. Variousaccuracyrateswereobtained in studiesconducted on stocks of somecompanies in the S&P 500 market withinthisscope.

KEYWORDS: LeNet-5, PSO, Machine learning , deeplearning , stock market prediction

---

Date of Submission: 17-01-2024 Date of acceptance: 31-01-2024

I. Introduction

Theterm 'Stock Exchange' is widelyused in manylanguagesand is generallyassociatedwithfinancialmarkets. InTurkish, theword 'borsa' is derivedfromtheItalianword 'bourse,' meaning 'exchange.' A stockexchange is a market wherefinancialassets (such as stocks, bonds, commodities, currencies, etc.) areboughtandsold. 'StockPrediction' is a conceptused in financialanalysisandvaluationprocesses. Stockprediction is an analyticalprocessthatattemptstoforecastthefuturestockperformance of a specificcompany. Investors, financialanalysts, andotherfinanceprofessionalsoftenusestockpredictionstomakeinvestmentdecisionsorformulateportfolio strategies.

Deeplearning is a subfield of machinelearning, which is a branch of artificialintelligence. Inapplicationsrelatedtostocksandfinancialmarkets, deeplearning can offerpotentialadvantages in areassuch as pricepredictions, developingtradingstrategies, and risk management. However, theapplication of deeplearningmodels in financialmarketsmayfaceseveralchallenges. Thecomplexity of financialmarkets, uncertainty, andsuddenchanges can impacttheaccuracy of models. Additionally, thedynamicnature of data sets in financialmarketsmayrequireconstantupdatesandadjustmentstothemodels.

Therefore, accuratemodelingusingprecise data is crucial in creating a reliablepredictionandtradingalgorithm. Inthisstudy, data obtainedfromselectedcompanies in the S&P 500 market werelabeled, convertedinto 2D imagematrices, andusedtocreate a buy/sellalgorithmbased on LeNet-5-based CNN networks. Variousaccuracyrateswereachieved in thetradingalgorithm, depending on thespecificstock data. (Theseratesmayvarydepending on thestock data used.)

1.1. Related Works

Inseveralstudiesconducted on thissubject, variousadvantagesanddisadvantageshavebeenidentified. Forinstance, in thearticle by J. Eapen et al.a performanceimprovement of 9% wasachieved; however, certainchallenges in theapplicationwerealsonoted.
[1]Anotherstudyemploying SI-RCNN andotherhybridmodelsdemonstratedbetterperformance but couldgenerateinaccuratepredictions in largedatasets.[2]In a studyusing LSTM and RMSE modelstheobtained model exhibitedhighdecision-makingspeedandlowerrorrates, albeitrequiringsignificantresourceusageforextensive datasets. [3]

Conversely, in a studyutilizing RNN networksandAdaGrad a model with a remarkablylowerror rate wasobtained, but itsfocus on preciseaccuracywashinderedbythenecessityforextensive data.[4]In an RNN and LSTM-basedstudya highaccuracy rate (83.88%) wasachieved, but the risk of overfittingnecessitatedeffortsforregularization.
[5]In a studyemploying Word2Vec, FastText, andGloVewith RNN LSTM models, althoughthe model exhibitedhighaccuracy, it wassusceptibletomanipulations, albeitfacilitatingease of trading.[6]Inanotherstudyusing MLPhighaccuracywasattained, but the model requiredmore data andfeaturesforsupport.[7]

A model supportedby ARIMA, AR, and ARMA algorithmsachievedhighaccuracyandpredictionrates, but occasionalinstances of overfittingwereencountered, castingdoubt on itsscientificaccuracy.[8]In a comparativestudy of RNN and CNN [8], while RNN performedbetter in prediction, nosignificantperformancedifferencewasfoundbetweenthetwomodels.[9]In a hybrid model involvingRelu, MLP, LSTM, andothermethodologiesscalingwasexcellent, but advancednormalization of data wasneededforimprovement in performance.[10]A model comprisingXGBoost, LR, EMA, SMA, andotherhybridmethodsexhibitedgoodpredictionperformance at variouslevels but demandedsubstantialtraining data.[11]

Inanother model involving RNN and LSTMexcellentpredictionresultswereobtained, yet the model requiredmultiplelayers, constitutingitsweakness.[12]In a studywiththemostaccurateandprecisepredictionthe model, based on LSTM, raisedconcerns as it inherentlypossessedalltheweaknessesassociatedwith LSTM, raisingdoubtsaboutitsoverallperformance.[13]In a studysupportedbyGenerativeAdversarial Network (GAN)a competitionbetweentwoneuralnetworks (LSTM and GAN) wasobserved. Although LSTM providedmoreaccurateresults, achieving optimal trainingwaschallenging[14]

In a model supportedby PSO-LSTMthe model performedquitewellcomparedtomanyartificialintelligencemodels, but therewas a needforfurtherdevelopment on a betterfoundation.[15]Inourstudy, combiningthis model withanother, weenhancedtheperformanceandprediction in a morescientificandvalidmanner. In a Merton-LSTM-basedstudydespitehighaccuracy, applicationdifficultiesnegativelyimpactedthemodel'sperformance[16]A studyutilizingsocialanalysistomeasureuserbehavior anddetermine market pricingthroughdecisiontreemethodhad high model accuracy, but itscomplexitynecessitatedfurtherdevelopment.[17]

In a model using EMD algorithmwhile self-learning, organizing, andinformationprocessingcapabilitieswerehigh, dependency on additionalfactorsweakenedthe model. [18]Inthis model based on DMLP, CNN, SVM, and RF, RF is a model initiallyproposedbyHo (1995), characterized as a parametricandnon-linear model. Duetoitsconsistentconvergence, this model effectivelymitigatestheissue of overfitting (Breiman, 2001). Leveragingtheadvantages of RF, it is commonlyemployedforstockpredictions. However, therobustperformanceaspect of thisstudyposesconsiderablechallengeswhenappliedtostockswithhightradingvolumes.[19]

Anotherstudyusing DMLP layeredwith CNN, RNN, and LSTM demonstratedease of workingwithlarge data andgoodperformance, but it carriedthe risk of losingrelationships. [20]In an image-basedstudywhere data wasconvertedtoimagesandthenprocessedwith CNN and LR, whileperformanceimproved, challenges in analysisemerged.[21]In an LSTM-basedstudydespiteachievingbettervariationdetection andobtaining a model thatdoes not requiredimensionreduction, theaccuracy rate wasconsiderablylow. [22]

TheMultilayerFeedforwardNeural Network (MFNN) is a connectedArtificialNeural Network withmultiplelayersthatconsist of neuronsassociatedwithweightsandcalculatetheoutputusingactivationfunctions. Inthisstudybased on MFNN andStochasticGradientDescent (SGD), whiletheperformancequality is quitegood, it is significantlyinfluencedbysignalquality. [23]

Inthisstudy, one-dimensional data convertedintotwo-dimensional data wasusedtocreateConvolutionalNeural Networks (CNNs), resulting in highprecisionandaccuracy. However, thealgorithmemployedforpredictions is unabletoidentifythelowestandhighestETFs; thus, optimization is required.[24]Thisstudy is alsoone of thetwostudiesuponwhichourresearch is based. Inthisstudybased on RNN-LSTM, moreconsistentresultsareobtained; however, it requiresworkingwith a greateramount of categorical data. [25].

II. Metodology

Inthispaper, weutilizedtheParticleSwarm Optimization (PSO) algorithmforthe optimization of thehyperparameters of the LeNet-5 model. Thepurpose of the LeNet model is theverification of signaturestrainedwiththe IMAGENET database. Consequently, weoptimizedthehyperparameters of the LeNet-5 model toreceive buy/sellorders. Theschematicrepresentation of theproposedmethod is presentedbelow.

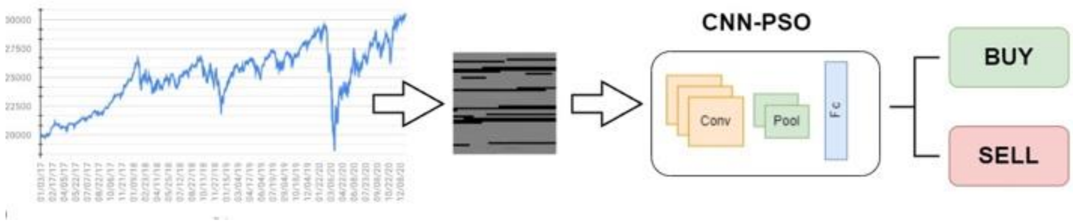


Figure-1: CNN-PSO WorkflowDiagram

a. LeNet5

ConvolutionalNeural Network (CNN) is a type of neural network architecturedesignedforimageandvisual data processing. It is particularlyeffective in taskssuch as imagerecognition, objectdetection, andimageclassification. CNNsuseconvolutionallayerstoautomaticallyandadaptivelylearnspatialhierarchies of featuresfrominput data. ConvolutionalLayers: Theselayersapplyconvolutionoperationstoinput data usingfiltersorkernelstoextractfeatures. Convolutionhelpsthe network recognizepatternssuch as edges, textures, andmorecomplexstructures. PoolingLayers: Poolinglayersreducecomputationalcomplexitybysubsamplingthespatialdimensions of input data andpreservingimportantfeatures. Commonpoolingoperationsincludemaximumpooling, whichretainsthemaximum value in a region, andaveragepooling, whichcomputestheaverage. FullyConnectedLayers: Aftermultipleconvolutionalandpoolinglayers, thehigh-levellogic in theneural network is capturedbyfullyconnectedlayers. Theselayersutilizethelearnedfeaturestomakepredictions.

$S(i,j) = (I \times K)(i,j) = \Sigma m \Sigma n\, I(m,n).K\,(i-m,j-n)(1)$

S(i, j): Output of theconvolutionoperation at position (i, j)
I(m, n): Pixel of theinputimage at position (m, n)
K(i-m, j-n): Convolutionkernel (filter) at position (i-m, j-n)

Insummary, CNNsarepowerfulneural network architecturesthatleverageconvolutionaloperationstoautomaticallylearnhierarchicalfeaturesforprocessingandanalyzingvisual data. Theformulaillustratesthefundamentalconvolutionoperation, a keyprocessforfeatureextraction in CNNs.

ReLU, whichstandsforRectifiedLinearUnit, is a widelyusedactivationfunction in artificialneuralnetworks, includingConvolutionalNeural Networks (CNNs) anddeeplearningmodels. TheReLUfunctionintroducesnon-linearitytothe network, enabling it tolearncomplexpatternsandrepresentations in the data. TheReLUfunction is defined as follows:
$ReLU(X) = \max(0,x)(2)$

Insimpleterms, foranyinput x, theReLUfunctionoutputs

x if x is positive, andthe
output is 0 otherwise

Thisactivationfunction has become popular duetoitssimplicityandeffectiveness in trainingdeepneuralnetworks. Non-linearity: ReLUintroducesnon-linearitytothe network, allowing it tolearnandapproximatecomplex, non-linearrelationships in the data. Efficiency: Thesimplicity of ReLUmakes it computationallyefficientwhencomparedtosomeother activationfunctions. SparseActivation: ReLUtendstoproducesparseactivation, meaningthatonly a subset of neurons in a layerareactivated. This can be beneficial in terms of computationalefficiencyand model capacity. However, it is importanttonotethatReLU is not withoutpotentialissues, such as the "deadReLU" problem whereneurons can becomeinactiveduringtrainingand halt learning. Variants of ReLU, such as LeakyReLUandParametricReLU, havebeenintroducedtoaddresssome of thesechallenges. LeNet-5 is a convolutionalneural network (CNN) architecturedesignedbyYannLeCunandcolleaguesfor handwrittendigitrecognition. Itwasone of thepioneering CNN architecturesandplayed a significant role in thedevelopment of convolutionalneuralnetworks. LeNet-5 consists of twoconvolutionallayers, eachfollowedby a subsampling (pooling) layer. Theselayershelpthe network learnhierarchicalrepresentations of inputimages. ActivationFunction: Thenon-linearactivationfunctionused in LeNet-5 is the sigmoid activationfunction. FullyConnectedLayers: Aftertheconvolutionalandpoolinglayers, LeNet-5 has threefullyconnectedlayers. Theselayerscontributetohigh-levelreasoninganddecision-makingbased on thelearnedfeatures. The final layer of LeNet-5 is a softmaxlayerthatprovidesprobabilityscoresfordifferentclasses, commonlyusedformulti-classclassificationtasks. LeNet-5 wasinitiallydesignedforhandwrittendigitrecognition on 32x32 pixelgrayscaleimages. Itdemonstratedtheeffectiveness of CNNs in imagerecognitiontasksandlaidthefoundationformore complexarchitecturesused in modern deeplearningapplications. Whileinitiallydevelopedfordigitrecognition, itsprinciplesinfluencedthedesign of subsequent CNN architecturesforvariouscomputervisiontasks.

b. Optimization Algorithms

i. ParticleSwarm Optimization (PSO)

It is a computational optimization techniqueinspiredbythesocialbehaviors of organisms, particularlybirds. InParticleSwarm Optimization (PSO), potentialsolutionsto a problem arerepresented as particlesthatmove in thesolutionspace, adjustingtheirpositionsbased on theirownexperiencesandtheexperiences of otherindividuals in thegroup, especiallybirds. Theobjective is tofindthemostsuitablesolutionto a specific problem. PSO is commonlyemployed in variousdomainsfor optimization tasks

$velocityi\ (t+1) = w \times velocityi(t) + c1 \times r1 \times (pbesti - positioni(t)) + c2 \times r2 \times (gbest - positioni(t))$(3)
velocityi (t+1) representstheupdatedvelocity of particle i at time t+1

$positioni(t+1) = positioni(t) + velocityi\ (t+1)$ (4)
positioni(t+1) denotestheupdatedposition of particle i at time t+1.

ii. **Adam**Optimizer

Adam (Adaptive Moment Estimation) is a widelyused optimization algorithm in machinelearningfortrainingdeepneuralnetworks. Itcombinesideasfrom Momentum andRMSpropanddynamicallyadjustslearningratesforeachparameter. Adam is knownforitsefficiency, fastconvergence, andabilitytohandlesparsegradients. Bycomputingadaptivelearningratesbased on thefirstandsecondmoments of gradients, it enableseffective optimization in variousmachinelearningtasks.

$Mt = \beta1 . mt - 1 + (1 - \beta1). \nabla Jt(\theta)$(5)

$Vt = \beta2 . vt - 1 + (1 - \beta2). \left(\nabla Jt(\theta)\right)^2$(6)

$\widehat{m}t = \frac{m_t}{1-\beta_1^t}$(7)

$$\hat{v}t = \frac{v_t}{1-\beta_2^t} \quad (8)$$

$$\theta t + 1 = \theta_t - \alpha . \frac{\hat{m}_t}{\sqrt{\hat{v}_t + \varepsilon}} \quad (9)$$

θ: Model Parameters
α: LearningRate
J_t: It is thegradient of theobjectivefunctionwithrespecttotheparameters at time t.
β_1 ve β_2: Exponentialdecayratesforthefirstandsecondmoments
m_t: first moment(averages ofgradients)
v_t: secondmoment (meansquaredgradient)
t: time
$\hat{m}_t$: adjustedfirstmoment
$\hat{v}_t$: adjustedsecondmoment
ε: a smallconstantaddedtothedenominatorfornumericalstability (usually10^{-8})

III. Experimental Results

Inthissection, wepresentedtheexperimentalresults of thestocktradingordersappliedusingthe KERAS platform.

a. DatasetandEditing

Inthisstudy, weutilizedthedatasetconsisting of thestock data of Netflix (NFLX), Boeing Corp. (BA), and Amazon (AMZN) fromthe S&P 500 stocks. Thisdatasetincludes 7 parametersforeachstock: date, low value, opening value, tradingvolume, dailyhigh value, closing value, andadjustedclosing value. Tofacilitatetheunderstandingandprocessing of the data, it is necessarytosubjectthe data to a certainorganization. Therefore, labeling of thevalues is required. Inthisstudy, weusedthelabelingtype of 1/0 Buy/Sell (1: buy, 0: sell). This has facilitatedtheunderstandingandprocessing of the data. Intradingandinvestment, analystsoftenusetechnicalanalysistodeterminepotentialentry (buy) andexit (sell) pointsfor a financialinstrument. Thisanalysisinvolvesexaminingpastpricecharts, technicalindicators, andotherfactorstomakepredictionsaboutfutureprice movements. Buy andsellsignalsareindicatorsortriggersthatmayindicate a good time toenterorexit a position. Inthiscontext, labelingthe data using buy/selllabelingor 1/0 labeling is necessarytoprocessthe data andobtainaccurateresults. Buy/Selllabeling is a binarylabelingmethod, where a signal of 1 indicates a buy, and a signal of 0 indicates a sell.

1 to 10 of 5176 entries Filter

Date	Low	Open	Volume	High	Close	Adjusted Close	Label
2002-05-23	1.1457140445709229	1.1564290523529053	104790000	1.2428569793701172	1.1964290142059326	1.1964290142059326	0.0
2002-05-24	1.1971429586410522	1.214285969734192	11104800	1.225000023841858	1.2100000381469729	1.2100000381469729	0.0
2002-05-28	1.157142996788025	1.2135709524154663	6609400	1.2321430444717407	1.157142996788025	1.157142996788025	0.0
2002-05-29	1.0857139825820925	1.1642860174179075	6757800	1.1642860174179075	1.1035710573196411	1.1035710573196411	0.0
2002-05-30	1.0714290142059326	1.1078569889068604	10154200	1.1078569889068604	1.0714290142059326	1.0714290142059326	0.0
2002-05-31	1.0714290142059326	1.0785709619522097	8464400	1.0785709619522097	1.076429009437561	1.076429009437561	0.0
2002-03-06	1.076429009437561	1.0800000429153442	3151400	1.1492860317230225	1.1285710334777832	1.1285710334777832	0.0
2002-04-06	1.1107139587402344	1.135714054107666	3105200	1.1399999856948853	1.1178569793701172	1.1178569793701172	0.0
2002-05-06	1.1071430444717407	1.1107139587402344	1531600	1.1592860221862793	1.147143006324768	1.147143006324768	0.0
2002-06-06	1.1485710144042969	1.149999976158142	2305800	1.2321430444717407	1.182142972946167	1.182142972946167	0.0

a. Labeled data pertainingto Netflix

labeled_stock_data_amzn.csv

1 to 10 of 6438 entries Filter

Date	Low	Open	Volume	High	Close	Adjusted Close	Label
1997-05-15	0.0963540002703666	0.1218750029802322	1443120000	0.125	0.0979169979691505	0.0979169979691505	0.0
1997-05-16	0.0854170024394989	0.0984380021691322	294000000	0.0989580005407333	0.0864579975605011	0.0864579975605011	0.0
1997-05-19	0.0812499970197677	0.0880210027098655	122136000	0.0885419994592666	0.0854170024394989	0.0854170024394989	0.0
1997-05-20	0.0817710012197494	0.0864579975605011	109344000	0.0874999985098838	0.0817710012197494	0.0817710012197494	0.0
1997-05-21	0.0687500014901161	0.0817710012197494	377064000	0.0822919979691505	0.0713540017604827	0.0713540017604827	0.0
1997-05-22	0.0656249970197677	0.0718749985098838	235536000	0.0723960027098655	0.0697920024394989	0.0697920024394989	0.0
1997-05-23	0.0666669979691505	0.0703129991889	318744000	0.0760419964790344	0.0750000029802322	0.0750000029802322	0.0
1997-05-27	0.0729169994592666	0.0755209997296333	173952000	0.0822919979691505	0.0791670009493827	0.0791670009493827	0.0
1997-05-28	0.0765630006790161	0.0812499970197677	91488000	0.0817710012197494	0.0765630006790161	0.0765630006790161	0.0
1997-05-29	0.0739580020308494	0.0770829990506172	69456000	0.0770829990506172	0.0752599984407424	0.0752599984407424	0.0

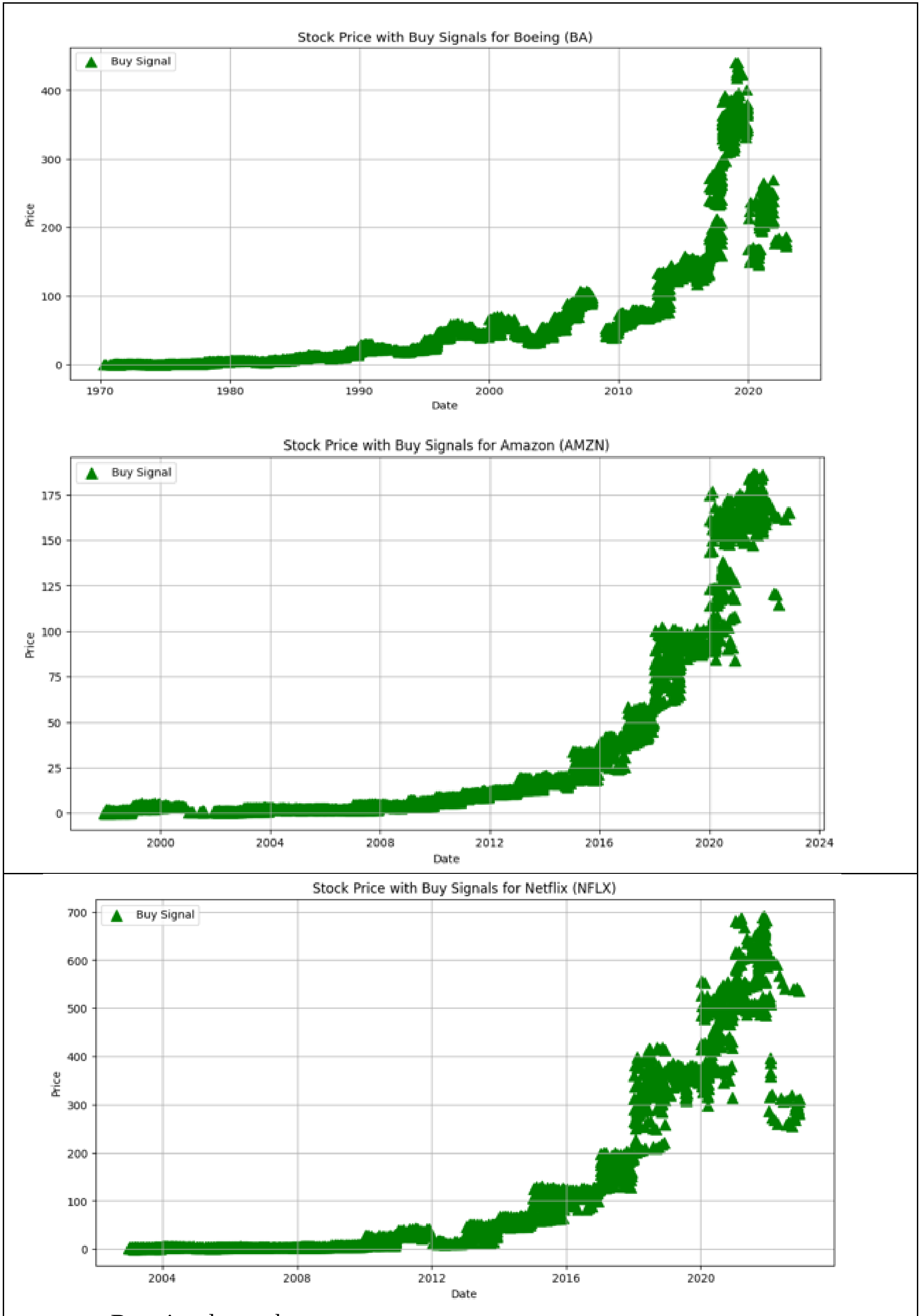
b. Labeled data pertainingto Amazon

1 to 10 of 13356 entries Filter

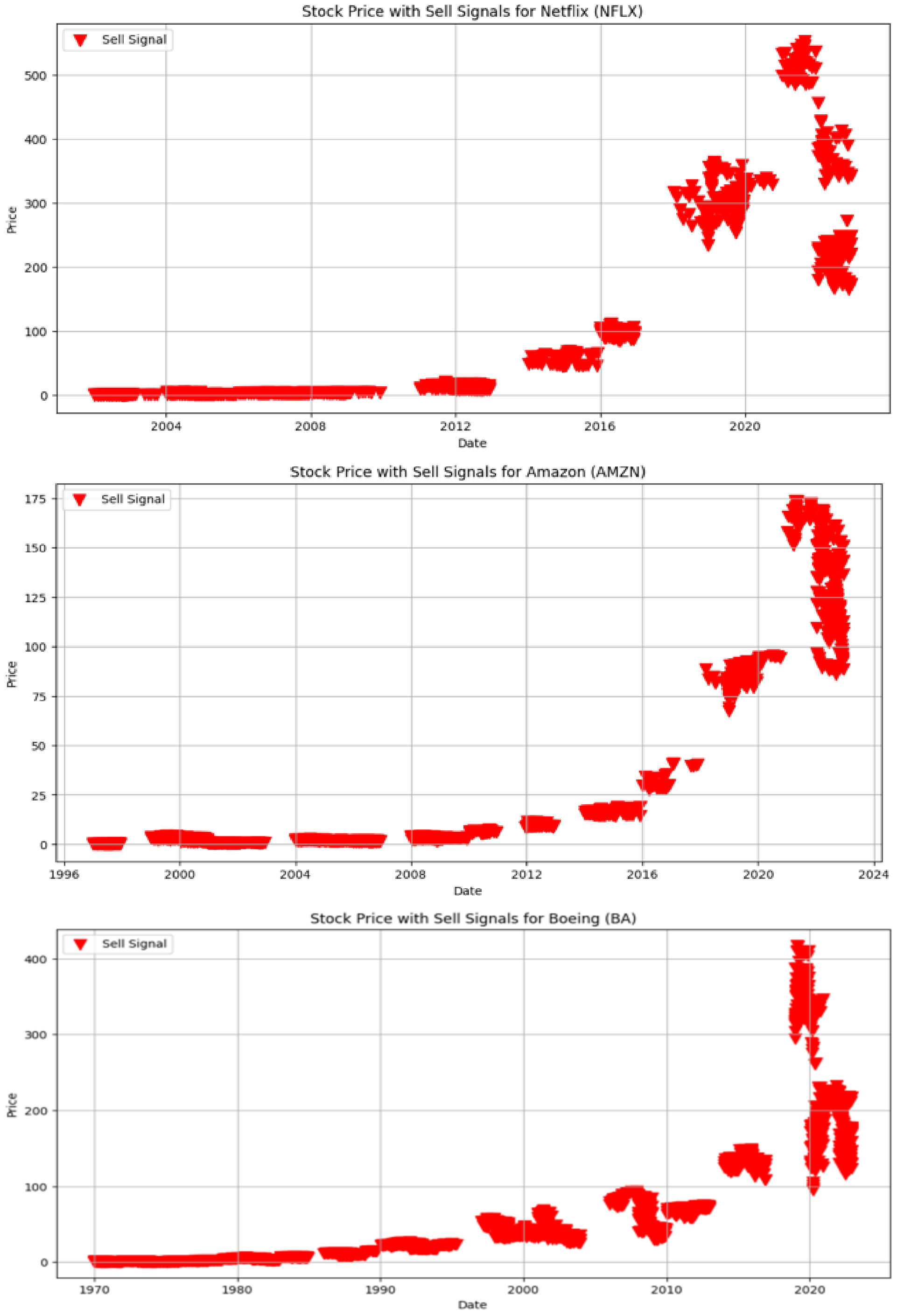
Date	Low	Open	Volume	High	Close	Adjusted Close	Label
1970-02-01	0.9259260296821594	0.9259260296821594	634838	0.979423999786377	0.979423999786377	0.290567398071289	0.0
1970-05-01	1.0082299709320068	1.0082299709320068	741150	1.0246909856796265	1.0164610147476196	0.3015552461147308	0.0
1970-06-01	1.0246909856796265	1.0246909856796265	1354725	1.0493830442428589	1.0288070440292358	0.3052180111408233	0.0
1970-07-01	1.020576000213623	1.0288070440292358	646988	1.0452669858932495	1.0329220294952393	0.3064388036727905	0.0
1970-08-01	1.0082299709320068	1.0329220294952393	807975	1.037037014961243	1.020576000213623	0.3027762174606323	0.0
1970-09-01	0.9958850145339966	1.020576000213623	634838	1.0329220294952393	0.9958850145339966	0.2954510748386383	0.0
1970-12-01	0.979423999786377	0.9958850145339966	568013	1.0	0.9876539707183838	0.2930091619491577	0.0
1970-01-13	0.9341560006141664	0.9835389852523804	883913	0.9835389852523804	0.9382719993591307	0.2783587872982025	0.0
1970-01-14	0.9135800004005432	0.9341560006141664	1105650	0.9341560006141664	0.9300410151481628	0.2759170830249786	0.0
1970-01-15	0.9053500294685364	0.9259260296821594	1436738	0.9259260296821594	0.9094650149345398	0.2698125839233398	0.0

c. Labeled data pertainingto Boeing

Figure-2: Labeled Data



a. Buy signalsovertheyears



b. Sellsignalsovertheyears

Figure-3:Buy andsellorders in thestockover time

Inordertoaccuratelyinterpretthe data andperformmachinelearning, one-dimensionallabeled data wastransformedinto 10x10 squarematriximagesbased on thelabel, whereeachsignalcorrespondsto a cell. Inthe initial stage, a general imagewascreatedtovisualizeallthe data

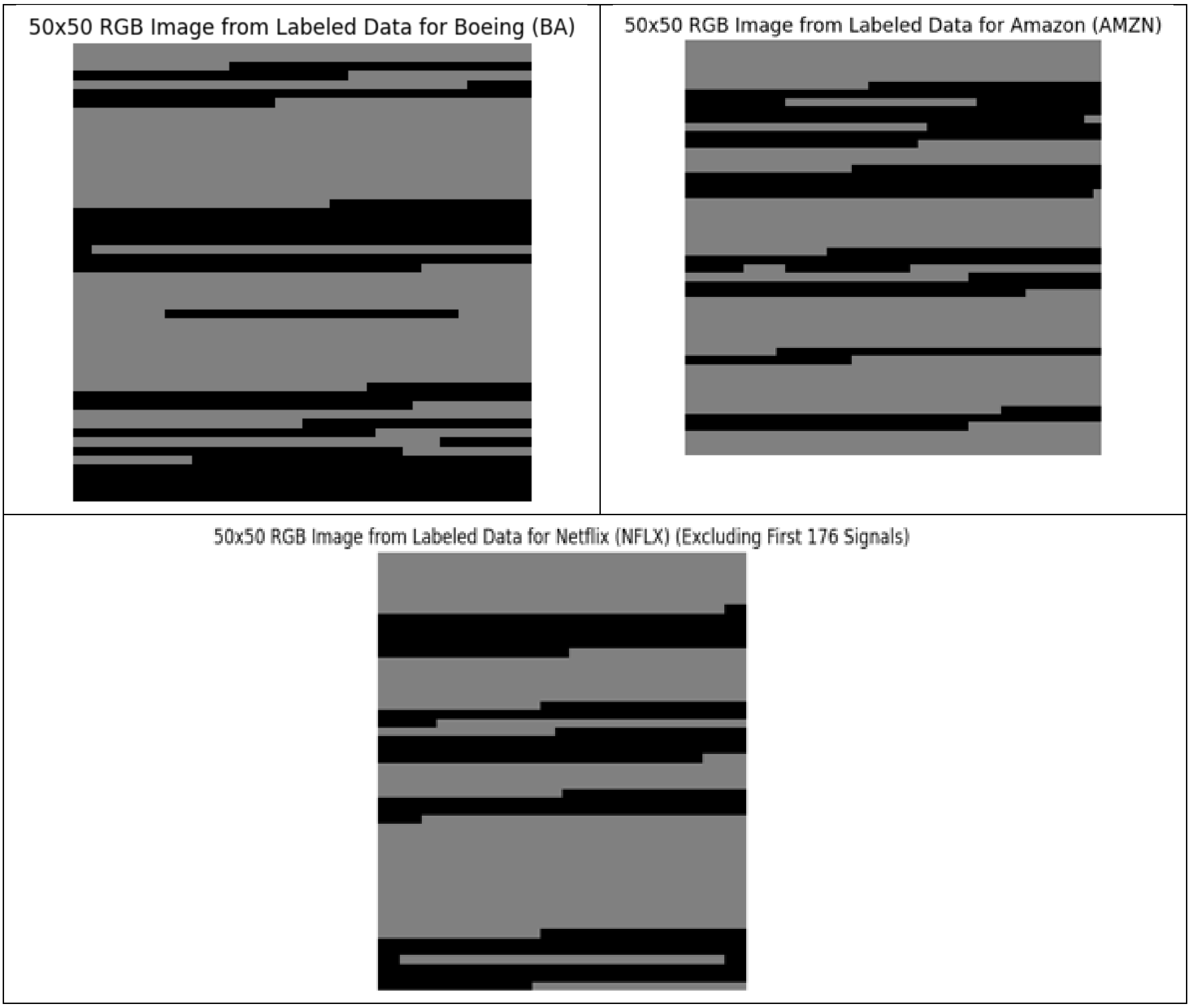
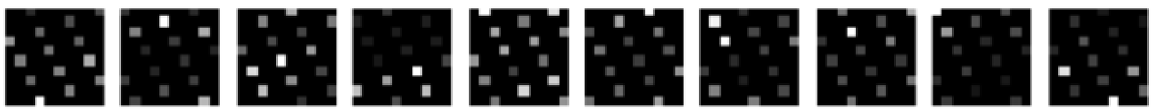
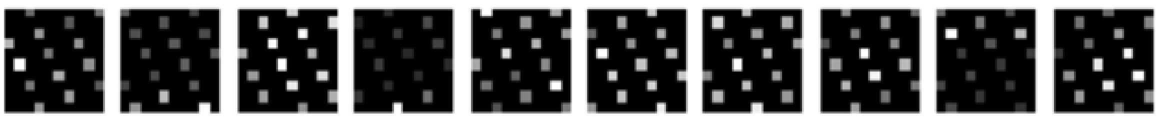


Figure-4: General Image Matrices

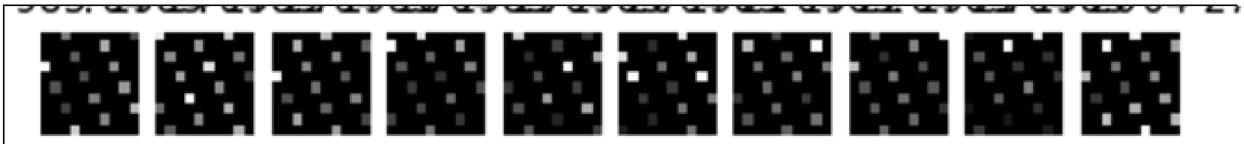
Subsequently, this general imagematrixwasorganizedtocreatedetailed 10x10 imagessuitableformachinelearning. Eachpixel here representsoneday.



a. Theimagematrixrelatedto Netflix



b. Theimagematrixrelatedto Amazon



c. Theimagematrixrelatedto Boeing

Figure-5: 10 ×10 Image Matrices

Thus, 2-dimensional visual data suitableformachinelearningstudieshavebeencreated

b. HyperparameterOptimization

Inthisproject, weuse PSO for optimization, andthetablebelowliststheparametersoptimizedwith PSO. Accordingtothis, thedensity of Netflix is significantlylowercomparedtoothers. Incontrast, themost dense layersareobserved in Amazon data. This is duetotherelativelyrecententry of Netflix intothe market anditsloweractivity. Boeing and Amazon, on theotherhand, havebeen in the market formanyyears, which has ledtohigherlayerdepths. Thehighdensity of layershelpsexplaincomplexrelationships.

Parameters	ValueLimits	Targetparametersselectedby PSO		
		Netflix	Amazon	Boeing
Dense Layer	[8- 128]	109	128	120
Dense Layer	[6- 64]	4	32	24
Adam optimization initialvalue	[0.0001- 0.1]	0.001	0.001	0.001

Table-1. Parameter optimizationboundaries.

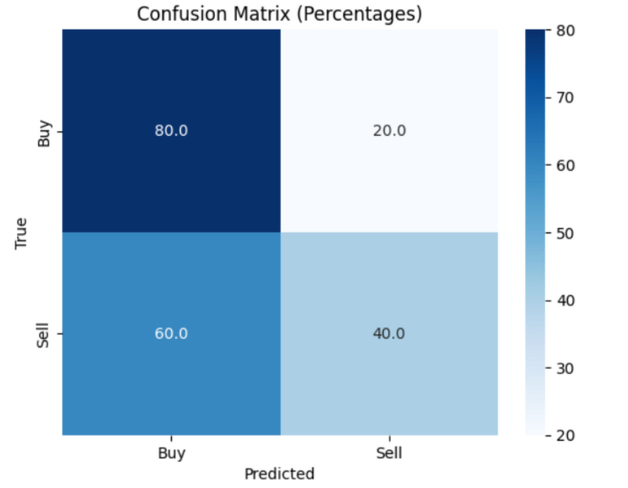
c. Theeffects of PSO on performance

Inthetablebelow, weutilized LeNet 5 withdefaultparametersandcompared it with LeNet-PSO. Alldeepmodelsaretrainedwith 30 epochsand a batch size of 16. Theaccuracyandprecision of modelscreatedwith PSO-optimized LeNet5 arehigher. However, therelativelylowincrease is mainlyduetothestock data used in thecomparison. Ifdifferentstockswereused, theseratioswould be morediverse. Whilethesensitivity rate increases in allstocksexcept Boeing, in thecase of Boeing data with LeNet5-PSO, it remainslowercomparedtothe model withonly LeNet5 applied. This is attributedtothecharacteristics of Boeing data, as thevolatility in the data alsoaffectsthe model performances.

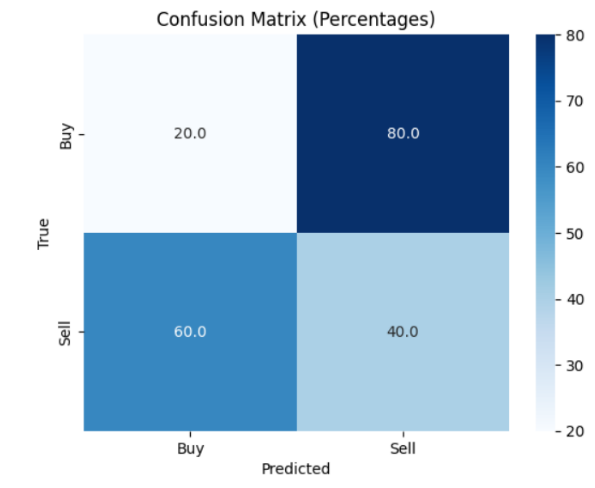
Table-2: Performance Metrics

Data ssssssResult	Netflix		Amazon		Boeing	
	LeNet 5	LeNet 5-PSO	LeNet 5	LeNet5-PSO	LeNet 5	LeNet 5-PSO
Accuracy	0.58	0.64	0.55	0.62	0.59	0.60
precision	0.39	0.42	0.41	0.54	0.55	0.63
recall	0.61	0.65	0.57	0.59	0.57	0.52
f1-score	0.49	0.51	0.51	0.66	0.61	0.44

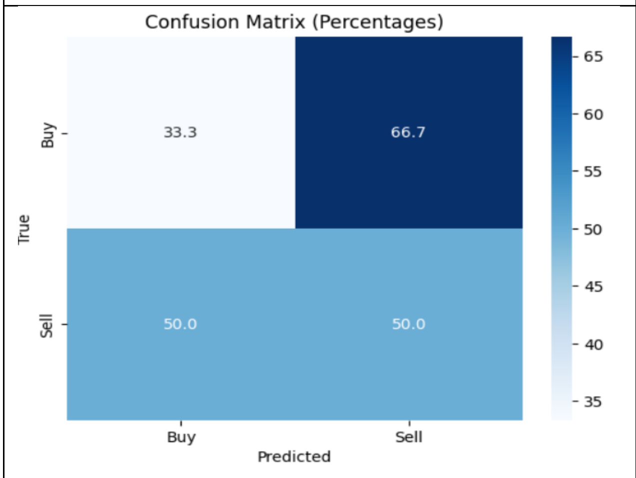
Theconfusionmatrixpresentedbelowdemonstratesthatthenumber of purchasesidentified as sales in the Netflix stock is 60 in boththeoptimizedanddefaultnetworks (LeNet 5). However, thenumber of purchasesidentified as purchaseswiththedeeplearning-optimized network is improvingto 80 comparedto 20 in thedefault network. Similarly, in thecase of Amazon, the model optimizedwithdeeplearningshows a relativelybetter value forpurchases, 33.7 comparedto 25 in thedefault model. However, there is nochange in theidentifiedsales. For Boeing, whilethedefaultmodel'spurchasecount is 61.5, it has decreasedto 55.6 in theoptimized model. Incontrast, thesalescount has increased in theoptimized model. Thereasonforthis is thevolatility, alsoknown as fluctuations, in Boeing stocks, which is highercomparedtotheothertwostocks.



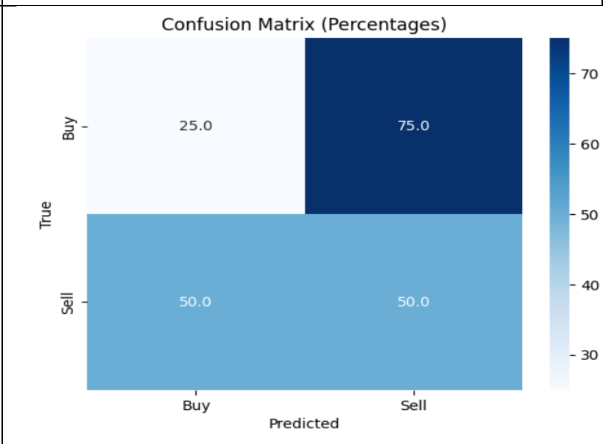
I. LeNet5-PSO (Netflix)



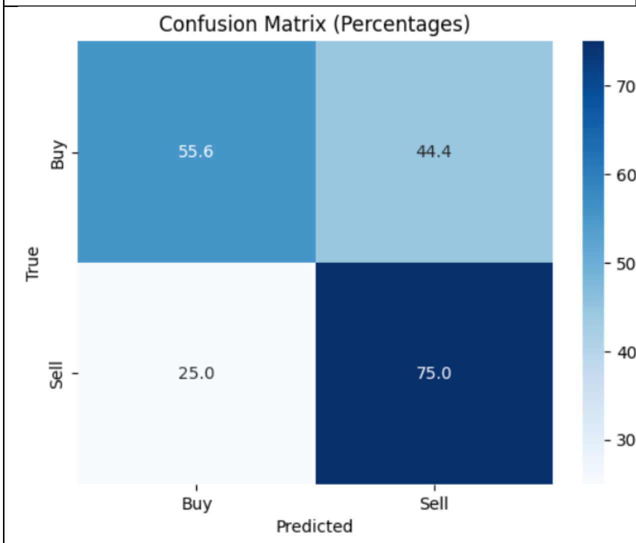
I. LeNet5 (Netflix)



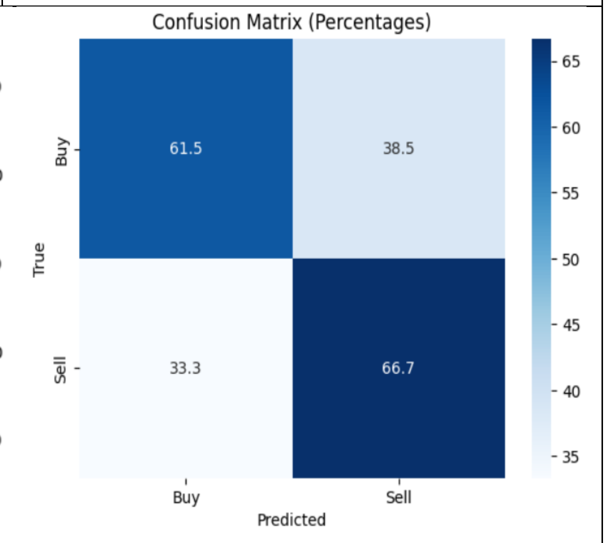
I. LeNet5-PSO (Amazon)



/. LeNet5 (Amazon)



/. LeNet 5-PSO (Boeing)



I. LeNet5 (Boeing)

Figure-6: ConfusionMatrices

IV. Results and Discussion

Inthisstudy, it is observedthatthe buy-sellmodelscreatedbased on LeNet5-PSO providehigheraccuracycomparedtoothermodels. Forexample, consideringonlythe model createdwith LeNet5, theaccuracy rate in Netflix stocks is 58%, while in the model optimizedwith PSO, it is 64%. In Amazon stocks, theaccuracy is 55% withonly LeNet5, whereas it reaches 62% in the PSO-optimized model. In Boeing stocks, whilethe model with LeNet5 has an accuracy of 59%, theaccuracy in the PSO-optimized model is measured as 60%. Obtainingdifferentresultsforeachstockandtheconfusionmatrixyieldinggoodresults in someplacesandpoorresults in othersindicatethatthe LeNet5-PSO model is unstable, which is a significantdisadvantage. Infuturestudies, it is possibletomakevariousmodificationstothe model tomake it morestable.

References

[1]. D. A. V. J. Eapen, «Novel Deep Learning Model with CNN and Bi-Directional LSTM for Improved Stock Market Index Prediction,» Conference: 2019 IEEE 9th Annual Computing and Communication Workshop and Conference (CCWC) , 2019.

[2]. C. D. A. a. f. M.Vargas, «Deep Learning for Stock Market Prediction Using Technical Indicators and Financial News Articles,» 2018.

[3]. N. S. a. F. S. Banik, «LSTM based decision support system for swing trading in stock market,» Knowledge-Based Systems 239(2):107994, 2021.

[4]. S. S. I. J. a. f. K. Sutradhar, «Stock Market Prediction using Recurrent Neural Network's LSTM Architecture,» Conference: 2021 IEEE 12th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON), 2021.

[5]. A. G. a. f. P.S. Sisodia, «Stock Market Analysis and Prediction for Nifty50 using LSTM Deep Learning Approach,» Conference: 2022 2nd International Conference on Innovative Practices in Technology and Management (ICIPTM) , 2022.

[6]. Z. H. K. a. R. Duvar, «An Efficient Word Embedding and Deep Learning Based Model to Forecast the Direction of Stock Exchange Market Using Twitter and Financial News Sites: A Case of Istanbul Stock Exchange (BIST 100),» IEEE Access 8:188186 - 188198, 2020.

[7]. H. K. M. Y. Z.H Kilimci, «Deep Learning-based Decision Integration Strategy for the Price Prediction of Istanbul Stock Exchange (BIST100),» 2021 13th International Conference on Electrical and Electronics Engineering (ELECO), 2021.

[8]. B. S. a. S. G. Rao, «Analysis of a Stock Exchange and Future Prediction Using LSTM,» "2021 4th International Conference on Recent Trends in Computer Science and Technology (ICRTCST), Jamshedpur, India, 2022, doi: 10.1109/ICRTCST54752.2022., pp. 48-54, 2022.

[9]. B. K. A.Aaryan, «Forecasting stock market price using LSTM-RNN,» 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), pp. 1557-1560, 2022.

[10]. N. P. A. Tsantekidis, «Using deep learning to detect price change indications in financial markets,» 2017 25th European Signal Processing Conference (EUSIPCO), Kos, Greec, pp. 2511-2515, 2017.

[11]. A. S. M. A. I. A. J. N. a. S. A. M. Biswas, «Predicting Stock Market Price: A Logical Strategy using Deep Learning,» 2021 IEEE 11th IEEE Symposium on Computer Applications & Industrial Electronics (ISCAIE), Penang, Malaysia, pp. 218-223, 2021.

[12]. P. N. H. J. S. S. a. A. M. M. Nabipour, «Predicting Stock Market Trends Using Machine Learning and Deep Learning Algorithms Via Continuous and Binary Data; a Comparative Analysis,» IEEE Access, vol. 8, pp. 150199-150212, 2020, doi: 10.1109/ACCESS.2020.3015966. , pp. 150199-150212, 2020.

[13]. H. E. M. S. J. a. D. R. K. J, «Stock Price Prediction Based on LSTM Deep Learning Model,» 2021 International Conference on System, Computation, Automation and Networking (ICSCAN), Puducherry, India, 2021, pp. 1-4, doi: 10.1109/ICSCAN53069.2021.9526491., pp. 1-4, 2021.

[14]. A. M. a. P. S. D, «Indian Stock Market Prediction using Deep Learning,» 2020 IEEE REGION 10 CONFERENCE (TENCON), Osaka, Japan, 2020, pp. 1215-1220, doi: 10.1109/TENCON50793.2020.9293712., pp. 1215-1220, 2020.

[15]. C. W. Y.-W. S. Qi-Qiao He, «LSTM with particle Swam optimization for sales forecasting,» Electronic Commerce

Research and Applications, Volume 51,, 2022.

[16]. H. Z. H. W. Y. L. H. W. Weifang Mao, «Forecasting and trading credit default swap indices using a deep learning model integrating Merton and LSTMs,» Expert Systems with Applications, Volume 213, Part B, https://doi.org/10.1016/j.eswa.2022.119012. , 2023.

[17]. D. R. D. B. C. Vaca, «Buy & Sell Trends Analysis Using Decision Trees,» DOI:10.1109/ColCACI50549.2020.9247907 Conference: 2020 IEEE Colombian Conference on Applications of Computational Intelligence (ColCACI), 2020.

[18]. B. Y. M. A. Yong'an Zhang, «A novel deep learning framework: Prediction and analysis of financial time series using CEEMD and LSTM,» Expert Systems with Applications, Volume 159, https://doi.org/10.1016/j.eswa.2020.113609. , 2020.

[19]. R. H. a. f. Yilin Ma, «Portfolio optimization with return prediction using deep learning and machine learning,» Expert Systems with Applications 10.1016/j.eswa.2020.113973, 2020.

[20]. O. B. S. A M Özbayoğlu, «Deep learning for financial applications : A survey,» Applied Soft Computing, Volume 93, 2020,, 2020.

[21]. K. I. a. f. A Nakayama, «Short-term Stock Price Prediction by Analysis of Order Pattern Images,» 2019 IEEE Conference on Computational Intelligence for Financial Engineering & Economics (CIFEr), Shenzhen, China, 2019, pp. 1-5, doi: 10.1109/CIFEr.2019.8759057., pp. 1-5, 2019.

[22]. A. P. R. A. O. D.M.O Nelson, «Stock market's price movement prediction with LSTM neural networks,» 2017 International Joint Conference on Neural Networks (IJCNN), Anchorage, AK, USA, 2017, pp. 1419-1426, doi: 10.1109/IJCNN.2017.7966019., pp. 1419-1426, 2017.

[23]. Z. L. L. C. W. Long, «Deep learning-based feature engineering for stock price movement prediction,» Knowledge-Based Systems, Volume 164, 2019,, 2019.

[24]. S. A. B. a. A. M. O. M. U. Gudelek, «A deep learning based stock trading model with 2-D CNN trend detection,» 2017 IEEE Symposium Series on Computational Intelligence (SSCI), Honolulu, HI, USA, 2017, pp. 1-8, doi: 10.1109/SSCI.2017.8285188., pp. 1-8, 2017.

[25]. K. K. a. S. J. T. Sanboon, «A Deep Learning Model for Predicting Buy and Sell Recommendations in Stock Exchange of Thailand using Long Short-Term Memory,» 2019 IEEE 4th International Conference on Computer and Communication Systems (ICCCS), Singapore, 2019, pp. 757-760, 2019.