A STOCK PRICE PREDICTION MODEL BASED ON INVESTOR SENTIMENT AND OPTIMIZED DEEP LEARNING

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Abstract:-- The MS-SSA-LSTM model improves stock prices for the use of multiple source data, emotional analysis, crew information methods and deep education. This model uses Money Control Forum Posting to create a Sentiment dictionary and index. This shines the effect of market spirit on stock prices. Sparrow Search Algorithm (SSA) optimizes LSTM hyperparameters to predict accuracy. Display tests reveal the superiority of the MSSA-LSTM model. This helps to predict stock prices properly. The algorithm Predicts short -term stock prices for India's chaotic financial sector, which helps investors to make dynamic decisions. LSTM+GRU Hybrid models were also introduced for classification of warehouses. A robust ensemble technique included a "Voting Classifier (AdaBoost + Random Forest) for sentiment analysis and a Voting Regressor (Linear Regression + Random Forest Regressor + K-Neighbors Regressor)" for stock price prediction. These ensembles easily merged with "MLP, CNN, LSTM, MS-LSTM, and MS-SSA-LSTM" models, improving predictive performance. A user-friendly Flask framework with SQLite support simplified signup, signin, and model evaluation for user engagement and testing.

"Index terms - Deep learning, LSTM model, stock price prediction, sentiment analysis, sentiment dictionary, sparrow search algorithm".

1. INTRODUCTION

The growing number of individuals in India is choosing towards invest in financial sector as a result of mature of stock market & rapid expansion of online finance. But there is a lot of data & a lot of volatility in stock market. It is important for many retail investors towards improve computer -life abilities. As a result, business & investors can equal benefit from more reliable stock price forecasts, which reduces investment risk & increases return on investment.

The first researchers who studied trends in share chain used statistical approaches towards create a linear model. Traditional approaches include Arma, Arima, Garch, so on. A survey of stock prices of time series is designed for [1] for arm. Arima model, which is taken from Arma, is used towards predict general direction of stock movements [2]. For a more accurate match for Shanghai Composite Index, Arima can also use model Wavelet analysis as well as [3]. Innovative concepts towards predict share chain on a temporary framework abide provided through GARCH model [4]. In addition, many academics have established theoretical support for volumetric value analysis of multi -compressing shares through creating a new prediction model connecting arm & garch [5]. These traditional approaches usually only work among common, structured data. On other hand, traditional prognosis is dependent on faith that rarely holds water in practice. As a result, it is problematic towards implement statistical methods towards mark non -linear economic data.

As a result, many academics try towards predict stock prices when using ML techniques such as nerve tights & support vector machines (SVMS). A basic principle of machine learning is employment of algorithms for data warning, learning & prediction. Many researchers use SVMs for stock forecasts because it has special utility in handling low-namuna size, high-dimensional data & non-linear scenarios. Compared towards statistical methods, Hussain & Naser [6] found that SVMs provide better stock prediction accuracy.

After finding that at least classes associated among genetic algorithm (GA) did better, Tea was et al. [[] A Hybrid SVM model proposed towards predict ups & downs of HS300 index. However, SVM's ability for mass assumption of stock data is forced through memory & treatment time This training is consumed when used on samples. Thereafter, problems of economic time chain abide addressed through using N & Multi-Lear N. Experimental evidence suggests that Ann stands out in two regions: fast convergence & excellent accuracy [8, 9], [10]. Through practical evaluation, Mogadam & Esfarinari [11] considered effect of several feed formators artificial nervous networks on market forecasts. towards increase BP (back proliferation) nerve rights, Liu & Hou used [12] Biecian's regularization method. However, there abide some methods where traditional nervous network methods can endure increased. Poor generality causes overfit & local adaptation. There is a need towards search for better models towards solve these problems, as it is necessary towards train many samples.

This research proposes a new model (MS-SSA-LSTM) towards predict share value that benefits from Sparrow Search algorithm & connects properties of LSTM nerve among data among multiple sources. Investors & traders can benefit from opportunity towards provide advance forecast for MS-SSA-LSTM share price forecast models. Businesses & investors use MS-SSA-LSTM model among data on specific equity they want towards buy, such as comments on stock market & transaction history. program predicts share value for next day & automatically generates a trend diagram.

2. LITERATURE SURVEY

S&P 500 & London Stock Exchange Returns & Volatility [1] presence & variations of ARMA models in long memory functions. Recently, multifractal analysis has become an important way towards understand complexity of financial market that cannot explain linear skilled market theory. In financial markets, a slightly effective market principle does not gradually mean - -related price returns. Prices should migrate randomly. Random walking hypothesis is compared towards uniforms & multifractality options. According towards several studies, instability of storage returns long distance, heavy tails & clustering. Self -like stochastic processes have long distance dependence & powerful tail, so multifractality modeling should include them. study estimates S&P 500 & London Stock Exchange Time Series Shares & provides monthly & annual return using ARMA model. [1] London Stock Exchange Statistical Investigation suggests that monthly arm model appears annually. Both S&P 500 & London Stock Exchange Boom & Bust abide effective & economically stable under bust.

The paper indicates how ARIMA time series model is used towards forecast Indian browser gold expenses from November 2003 towards January 2014 towards reduce gold shopping chance. Thus, towards propose traders on yellow metal purchases & sales. [2]As Indian economic system is slowed through means of political factors, international clues, & excessive inflation, researchers, investors, & speculators abide searching out monetary devices towards diversify their portfolios & decrease hazard. Gold was as soon as solely offered for weddings & other rituals in India, however now buyers value it, therefore it is important towards estimate its rate. GARCH & its many variations abide often used in economic literature & practice.

In quasi most chance estimation, innovations towards GARCH procedures abide taken into consideration towards endure identically & independently distributed among mean zero & unit variance (sturdy GARCH) [4]. Higher order dependence styles might endure used towards ex ante forecast GARCH improvements & inventory returns below much less restrictive assumptions (vulnerable GARCH, no unconditional correlation). Rolling home windows of empirical inventory returns abide applied towards test sequential GARCH innovation independence in this paper. Rolling -values from independence testing suggest serial dependence's time variant & might indicate stock charge movements one step ahead. When paired among independence diagnostics (-values) and/or linear return projections, nonparametric innovation predictions show ex ante forecasting advantages.

Financial Forecast GARCH type (particularly ARMA-GARCH) has been successful through using models & calculation-based approaches such as SVM & RVM. [2.6] Arma-Gorge, RSVM & RRVM abide used towards predict instability in this research. two garch approaches based on RSVM & RRVM abide compared towards parametric Garachs (Ren & Arma-Cauch) for multi-time forecast.

The model performance is measured among MSE, MAE, DS & linear regression r fucking. This analysis uses BSE Sensex & Nikkei225 data. This research analyzes how Outlair instability affects modeling & predictions. Our use suggests that RSVM & RRVM abide almost as better than a garch type model. Arma-Garre performs better than pure garch, & only RRVM Plus is strong in RSVM forecast. This research offers an EMD-LSSSVM model for CSI 300 index analysis. WD-LSSSVM (WAVELET supports minimum classes) is another goal for EMD-LSSSVM [7]. Different customization methods abide used, including simplex, GS (web search), PSO & GA, as parameter selection models abide important for performance. Experimental results suggest that EMD-LSSSVM model among GS algorithm predicts guidelines for stock market compared towards other techniques.

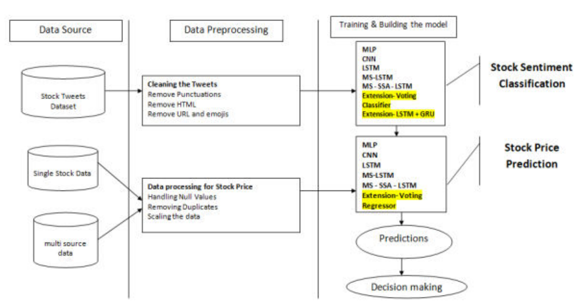
3. METHODOLOGY

i) Proposed Work:

The project presents state-of-the-art MS-SSA-LSTM stock price forecasting model. Swarm intelligence, sentiment analysis, & multi-source data abide harmoniously combined in this paradigm. [14,15,16,30] system can predict stock prices accurately through adjusting LSTM hyperparameters using Sparrow Search Algorithm. Its superiority over other models in experiments demonstrates its extensive application & potential towards enhance prediction performance. This model is compared towards "MLP, CNN, LSTM, MS-LSTM.". LSTM+GRU" hybrid models were also proposed for stock sentiment classification. A strong ensemble method consisted of a "Voting Classifier (AdaBoost + Random Forest) for sentiment & a Voting Regressor (Linear Regression + Random Forest Regressor + K-Neighbors Regressor)" for stock price prediction. These ensembles seamlessly integrated among "MLP, CNN, LSTM, MS-LSTM, & MS-SSA-LSTM" models, enhancing predictive performance. An easy-to-use Flask framework among SQLite enabled easy signup, signin, & model testing for user interaction & testing.

ii) System Architecture:

First, import Stock Tweets Dataset, Single Stock Data, & Multi-Source Data. These databases form foundation of sentiment analysis & stock price prediction. Stock Tweets Dataset text is cleaned of characters such as punctuations, HTML tags, URLs, & emoticons. This texts them before sentiment analysis. Processed Single Stock Data & Multi-Source Data eliminate duplicates, handle null values, & scale. This processes financial data before stock price forecast. For sentiment classification, "MLP, CNN, LSTM, MS-LSTM, MS-SSA-LSTM, Voting Classifier, & LSTM + GRU" abide modeled. Market sentiment is estimated among cleansed tweet data. "MLP, CNN, LSTM, MS-LSTM, MS-SSA-LSTM, & extension-Voting Regression" abide modeled for predicting stock prices. Stock price prediction using financial data. Financial data abide utilized towards forecast stock prices. Models predict after being trained. Market sentiment is exhibited through predictions in sentiment analysis. Stock price forecasting techniques approximate future prices. Sentiment analysis & stock price models aid traders & investors in making decisions. Results from combined data enable customers towards navigate dynamic stock market, minimize risks, & maximize returns.



“Fig 1 Proposed architecture”

iii) Dataset collection:

STOCK TWEETS DATASET

Tweets & other messages on social media belong towards stocks & create financial market for "shares tweets" data sets. among a view towards understanding public spirit of market news, we used it [1,4,7,8]. We were able towards use this information towards develop investment & stock trading solutions. through studying effect of social media on stock prices & market movements, we want towards provide useful information towards investors & traders. Thus, these abide five most important data set lines.

	Text	Sentiment
0	Kickers on my watchlist XIDE TIT SOQ PNK CPW B...	1
1	user: AAP MOVIE. 55% return for the FEA/GEED i...	1
2	user I'd be afraid to short AMZN - they are lo...	1
3	MNTA Over 12.00	1
4	OI Over 21.37	1

"Fig 2 Stock tweets dataset"

ALL STOCK DATASET

"All Stock Data Set" collects economic information from a wide selection of sources. For full stock market survey, it offers a tax of information. Using this dataset, stock price of our project was increased. Our goal was towards help companies & investors through making stock price estimates more accurate through using different types of data sources.

THIS IS SAMPLE DATASET

Date	Open	High	Low	Close	Volume
2012-01-03	325.25	332.83	324.97	663.59	7,380,500
2012-01-04	331.27	333.87	329.08	666.45	5,749,400
2012-01-05	329.83	330.75	326.89	657.21	6,590,300
2012-01-06	328.34	328.77	323.68	648.24	5,405,900
2012-01-09	322.04	322.29	309.46	620.76	11,688,800

"Fig 3 All stock dataset"

iv) Data Processing:

Data processing is process of creating useful information from raw data for companies. towards gather, organize, clean, verify, analyze, analyze & make data understandable formats, such as graphs or paper is part of all data processing. Manual, mechanical & electronic procedures abide three main options for data processing data. goal decision must make simple & more valuable information. Companies can then use this information towards make better strategic decisions & increase operations. This is a lot of help from automated data processing techniques including computer software development. towards better monitor quality of quality & towards make informed decisions, it can help in large data sets, especially through changing large data, in action -rich insights.

v) Feature selection:

When creating a model, functional choices abide required towards separate most important, consistent & non-respective features. As amount & diversity of dataset increases, it is important towards systematically reduce form. main purpose of convenience choices is towards reduce calculation costs for modeling through improving performance of a future indicative model at same time.

The function engineer depends on functional choice, which forces most relevant functions towards feed in ML algorithms. through removing over -clearing or insignificant properties & only keeping most important people, functional selection strategies abide reducing amount of input variables used through machine learning models. main benefits of taking time towards choose facilities before exercising machine learning model towards prioritize them.

vi) Algorithms:

The data is processed through a Multi layer perceptron (MLP) sequence of layers. As of data-solid entrance layer, network travels a series of hidden layers, where neurons weighted input yoga, non-lecture activation function app & later passes team passing. towards train network towards understand complex patterns in data, this weight is set between neurons. Provision or classifications abide generated through final output team. Because of their ability towards represent complex data conditions, MLP's use finds many applications, such as image recognition & financial forecasts. [1].

```
from sklearn.neural_network import MLPClassifier
mlp = MLPClassifier(random_state=1, max_iter=300)
mlp.fit(X_train, y_train)
y_pred = mlp.predict(X_test)
```

"Fig 4 MLP"

A type of deep teaching model that works well among data other than images is a Convolutional neural network (CNN). In order towards automatically learn important characteristics or patterns in data for network, data analyzes through layers that use dissolution & merger of operations. Time chain analysis & two examples of structured data processing applications have a great advantage from ability towards process CNN's sequential or online data. His extraordinary ability towards understand complex hierarchy & link is a reason for their adaptability in many areas, including economic prognosis & natural language treatment.

```
from tensorflow.keras import Sequential,utils
from tensorflow.keras.layers import Flatten, Dense, Conv1D, MaxPool1D, Dropout

def reg():

    model = Sequential()

    model.add(Conv1D(32, kernel_size=(3,), padding='same', activation='relu', input_shape = (X_train.shape[1],1)))
    model.add(Conv1D(64, kernel_size=(3,), padding='same', activation='relu'))
    model.add(Conv1D(128, kernel_size=(5,), padding='same', activation='relu'))

    model.add(Flatten())

    model.add(Dense(50, activation='relu'))
    model.add(Dense(20, activation='relu'))
    model.add(Dense(units = 1))

    model.compile(loss='mean_squared_error', optimizer='adam')

    return model
```

"Fig 5 CNN"

RNN is used among long short -term memory (LSTM) for sequential data analysis. LSTMS is good for applications among complex, remove data points because they can capture & preserve dependence on long sequences, unlike RNN. Specific memory cells & gates allow LSTM towards enable exact sequential patterns modeling, remember, update or forget. It is used in natural language treatment, speech recognition & financial time chain analysis, where previous backgrounds & potential patterns abide important.

```
# Initialising the RNN
regressor = Sequential()
# Adding the first LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50, return_sequences = True, input_shape = (X_train.shape[1], 1)))
regressor.add(Dropout(0.2))

# Adding a second LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50, return_sequences = True))
regressor.add(Dropout(0.2))

# Adding a third LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50, return_sequences = True))
regressor.add(Dropout(0.2))

# Adding a fourth LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50))
regressor.add(Dropout(0.2))

# Adding the output layer
regressor.add(Dense(units = 1))
```

"Fig 6 LSTM"

Extended LSTM neural networks like Multi-Source Long Short-Term Memory process data from several sources at a time as LSTM Neural Network. This integrates data from multiple sources towards handle extensive information, making it useful for difficult jobs as a share price prediction.

```
# Initialising the RNN
regressor = Sequential()
# Adding the first LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50, return_sequences = True, input_shape = (X_train.shape[1], 1)))
regressor.add(Dropout(0.2))

# Adding a second LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50, return_sequences = True))
regressor.add(Dropout(0.2))

# Adding a third LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50, return_sequences = True))
regressor.add(Dropout(0.2))

# Adding a fourth LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50))
regressor.add(Dropout(0.2))

# Adding the output layer
regressor.add(Dense(units = 1))
```

```
# Compiling the RNN
regressor.compile(optimizer = 'adam', loss = 'mean_squared_error')

# Fitting the RNN to the Training set
regressor.fit(X_train, y_train, epochs = 100, batch_size = 32)
```

"Fig 7 MS-LSTM"

The MS-SSA-LSTM model predicts stock prices among sophistication. It uses emotional analysis, multiple source data & sparrow sake towards customize Long Short -Term Memory (LSTM) network. This new approach predicts stock prices more accurately & firmly, & deals among financial forecast problems. It performs better than traditional models & is universally used, making it useful for investors & companies in unstable financial markets.

```
optimizer=SSA()
```

```
# Initialising the RNN
regressor = Sequential()
# Adding the first LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50, return_sequences = True, input_shape = (X_train.shape[1], 1)))
regressor.add(Dropout(0.2))

# Adding a second LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50, return_sequences = True))
regressor.add(Dropout(0.2))

# Adding a third LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50, return_sequences = True))
regressor.add(Dropout(0.2))

# Adding a fourth LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50))
regressor.add(Dropout(0.2))

# Adding the output layer
regressor.add(Dense(units = 1))
```

"Fig 8 MS-SSA-LSTM"

Voting regressor uses enchanted machine learning towards improve prediction through combining different regression techniques. It uses linear regression, random forest regressor & K-Neighbor's

Regressor. It collects predictions towards generate more accurate & strong regression models. This method uses linear regression lineary, flexibility in random forest & proximity-based learning of K-Nearest regression that improves future accuracy.

```
r1 = LinearRegression()
r2 = RandomForestRegressor(n_estimators=10, random_state=1)
r3 = KNeighborsRegressor()

eclf1 = VotingRegressor([('lr', r1), ('rf', r2), ('r3', r3)])
eclf1.fit(X_train, y_train)
y_pred = eclf1.predict(X_train)
```

“Fig 9 Voting Regressor”

A sophisticated Recurrent Neural network (RNN) design, LSTM+GRU, LSTM & GRU cells abide combined. Using LSTM's memory storage & calculation efficiency of GRU improves sequential pattern recognition of model. This combination time chain data, natural language processing & sequential patterns improve performance & exercise efficiency, as regardless of cell type restrictions.

```
model = Sequential()
model.add(Embedding(num_words, embed_dim,input_length = X_train.shape[1]))
model.add(LSTM(64,dropout=0.4, recurrent_dropout=0.4,return_sequences=True))
model.add(GRU(32,dropout=0.5, recurrent_dropout=0.5,return_sequences=False))
model.add(Dense(2,activation='softmax'))
model.compile(loss = 'categorical_crossentropy', optimizer='adam',metrics = ['accuracy',f1_m,recall_m,precision_m])
#print(model.summary())

trained5 = model.fit(X_train, Y_train, epochs = 20, batch_size=batch_size,validation_data=(X_test, Y_test),verbose = 1)
```

“Fig 10 LSTM + GRU”

The project uses Adaboost & Random Forest (RF) towards classify Sentiment voting classifies [18,39]. It uses AdaBoost boosting, which adds weak students towards a powerful classifies, & learns contingent of RF artists, who add predictions towards tree. Voting classifies improved classification accuracy & flexibility through incorporating these two methods, making it a valuable tool for market spirit analysis in our research.

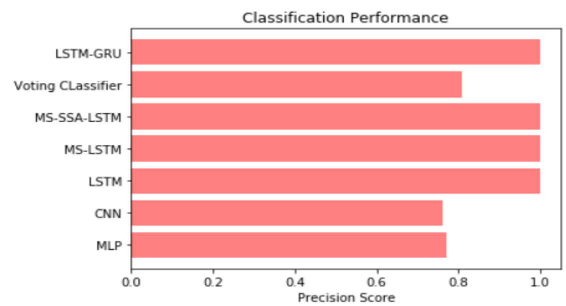
```
from sklearn.ensemble import RandomForestClassifier, VotingClassifier, AdaBoostClassifier
clf1 = AdaBoostClassifier(n_estimators=100, random_state=0)
clf2 = RandomForestClassifier(n_estimators=50, random_state=1)

eclf1 = VotingClassifier(estimators=[('ad', clf1), ('rf', clf2)], voting='soft')
eclf1.fit(X_train, y_train)
y_pred = eclf1.predict(X_test)
```

“Fig 11 Voting classifier”

4. EXPERIMENTAL RESULTS

Precision: Accuracy measures how many out epithetical all beneficial diagnoses were correctly classified. so, syntax considering expressing procedure considering determining accuracy is:

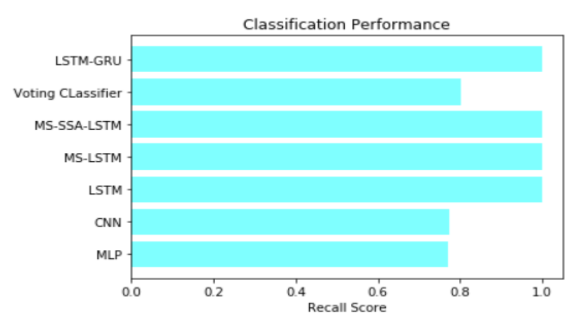
$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$



“Fig 12 Precision comparison graph”

Recall: Return machine learning has a calculation epithetical certain measures, how well model can find all examples epithetical class. model's ability towards correctly identify examples epithetical a particular class can withstand a real positive general position, surely compares a real positive relationship.

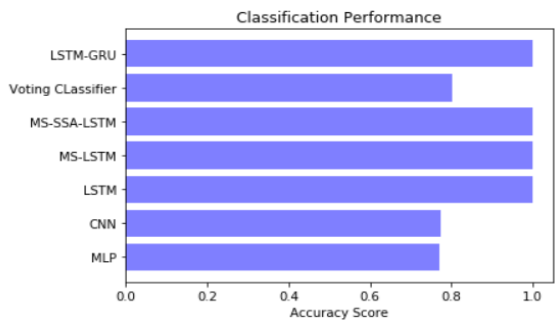
$$Recall = \frac{TP}{TP + FN}$$



“Fig 13 Recall comparison graph”

Accuracy: accuracy epithetical test is its ability towards properly distinguish patient & healthy cases. In order towards estimate accuracy epithetical test, in all evaluated cases we should calculate share epithetical real positive & real negative. Mathematically it can withstand it as.

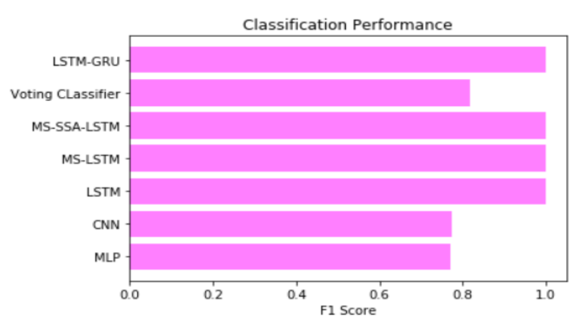
$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$



“Fig 14 Accuracy graph”

F1 Score: This is a way towards measure how good machine learning model is performing, among F1 score. Accuracy is part epithetical it, but model structure is ignored. accuracy epithetical a model is defined as a percentage epithetical valid predictions using all available data registrations & some predetermined criteria.

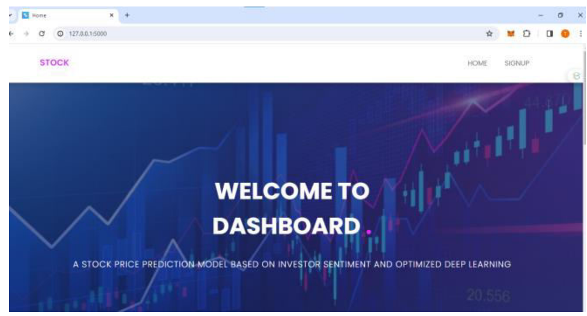
$$\text{F1 Score} = 2 * \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} * 100$$



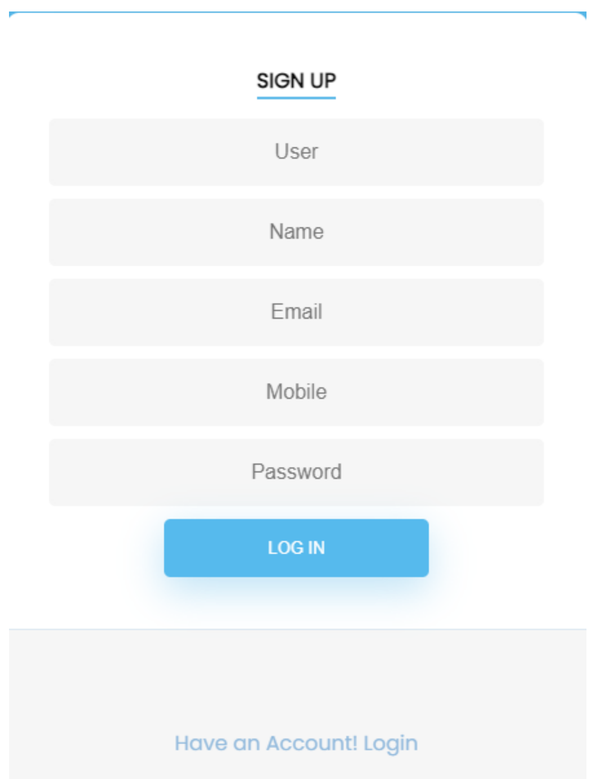
“Fig 15 F1Score”

	ML Model	Accuracy	Precision	Recall	F1-Score
0	MLP	0.771	0.771	0.771	0.770
1	CNN	0.773	0.761	0.773	0.774
2	LSTM	1.000	1.000	1.000	1.000
3	MS-LSTM	0.998	0.998	0.998	0.998
4	MS-SSA-LSTM	1.000	1.000	1.000	1.000
5	Extension- Voting Classifier	0.803	0.808	0.803	0.819
6	Extension- LSTM-GRU	1.000	1.000	1.000	1.000

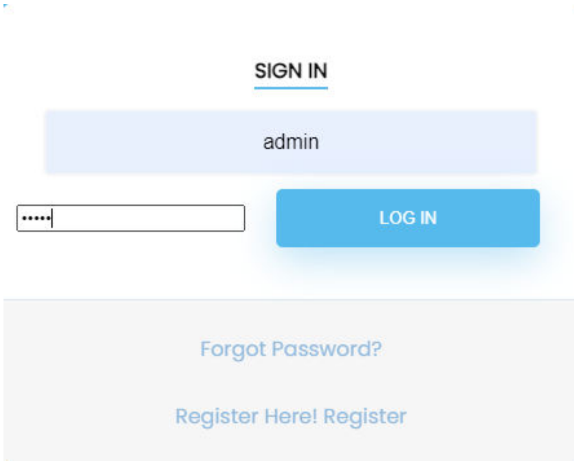
“Fig 16 Performance Evaluation”



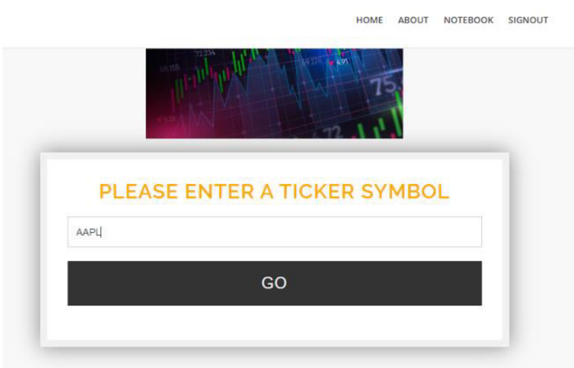
“Fig 17 Home page”



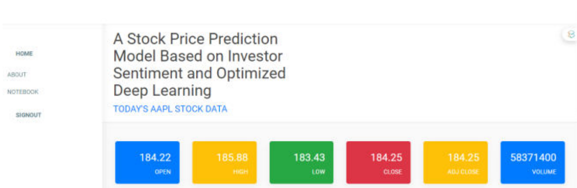
“Fig 18 Signin page”



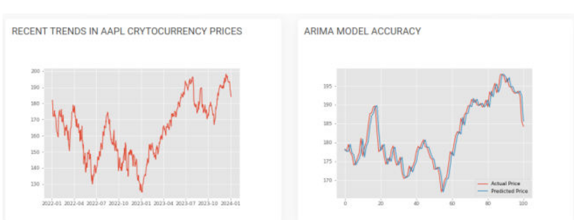
“Fig 19 Login page”



“Fig 20 User input”



“Fig 21 Result”



“Fig 22 Graphs”

“Fig 23 Graphs”

5. CONCLUSION

The MSSA-LSTM model was used towards improve predictions in stock market. emotional analysis & novel algorithm for prediction were exposed towards model [26]. MS-SSA-LSTM model distinguished itself in share value prediction & emotion classification. This reduced risk of using many data sources & advanced approaches & increased returns. "MLP, CNN, LSTM & MS-LSTM" were activated, but MS-SSA-LSTM improved them in short-term predictions for India's dynamic market. In expansion phase, "Voting Classifier, LSTM+GRU & Voting expanded Model" Prediction tools. " LSTM+GRU & Voting Regressor" were reliable alternatives towards predict spirit classification & share value. Flask addon made ticker symbol input easier for exact predictions. " LSTM+GRU was integrated" for " LSTM+GRU Spirit & Voting Regressor" for proportion of share value, user & investor's access was improved. Project forecast models & simple interfaces serve investors, traders & companies. MS-SSA-LSTM models & expansion reduce investment risk & improve decision in Dynamic Indian financial market.

6. FUTURE SCOPE

Adding real -time data input towards model can help investors make quick decisions. Integrating data sources in real time can endure advantageous. Integration of data from social media, news feed & macroeconomic indicators can provide a full market view & can increase accuracy of prediction. Tools or properties that models explain predictions can make it more transparent & user -friendly. Investors may benefit from forecasting explanations. Risk evaluation & portfolio optimization in model can help investors manage their investments overall. This may include diversification of assets & risk re -returns.

REFERENCES

[1] M. M. Rounaghi & F. N. Zadeh, ''Investigation of market efficiency & financial stability between S&P 500 & London stock exchange: Monthly & yearly forecasting of time series stock returns using ARMA model,'' Phys. A, Stat. Mech. Appl., vol. 456, pp. 10–21, Aug. 2016, doi: 10.1016/j.physa.2016.03.006.

[2] G. Bandyopadhyay, ''Gold price forecasting using ARIMA model,'' J. Adv. Manage. Sci., vol. 4, no. 2, pp. 117–121, 2016, doi: 10.12720/joams.4.2.117-121.

[3] H. Shi, Z. You, & Z. Chen, ''Analysis & prediction of Shanghai composite index through ARIMA model based on wavelet analysis,'' J. Math. Pract. Theory, vol. 44, no. 23, pp. 66–72, 2014.

[4] H. Herwartz, ''Stock return prediction under GARCH—An empirical assessment,'' Int. J. Forecasting, vol. 33, no. 3, pp. 569–580, Jul. 2017, doi: 10.1016/j.ijforecast.2017.01.002.

[5] H. Mohammadi & L. Su, ''International evidence on crude oil price dynamics: Applications of ARIMA-GARCH models,'' Energy Econ., vol. 32, no. 5, pp. 1001–1008, Sep. 2010, doi: 10.1016/j.eneco.2010.04.009.

[6] A. Hossain & M. Nasser, ''Recurrent support & relevance vector machines based model among application towards forecasting volatility of financial returns,'' J. Intell. Learn. Syst. Appl., vol. 3, no. 4, pp. 230–241, 2011, doi: 10.4236/jilsa.2011.34026.

[7] J. Chai, J. Du, K. K. Lai, & Y. P. Lee, ''A hybrid least square support vector machine model among parameters optimization for stock forecasting,'' Math. Problems Eng., vol. 2015, pp. 1–7, Jan. 2015, doi: 10.1155/2015/231394.

[8] A. Murkute & T. Sarode, ''Forecasting market price of stock using artificial neural network,'' Int. J. Comput. Appl., vol. 124, no. 12, pp. 11–15, Aug. 2015, doi: 10.5120/ijca2015905681.

[9] D. Banjade, ''Forecasting Bitcoin price using artificial neural network,'' Jan. 2020, doi: 10.2139/ssrn.3515702.

[10] J. Zahedi & M. M. Rounaghi, ''Application of artificial neural network models & principal component analysis method in predicting stock prices on Tehran stock exchange,'' Phys. A, Stat. Mech. Appl., vol. 438, pp. 178–187, Nov. 2015, doi: 10.1016/j.physa.2015.06.033.

[11] A. H. Moghaddam, M. H. Moghaddam, & M. Esfandyari, ''Stock market index prediction using artificial neural network,'' J. Econ., Finance Administ. Sci., vol. 21, no. 41, pp. 89–93, Dec. 2016, doi: 10.1016/j.jefas.2016.07.002.

[12] H. Liu & Y. Hou, ''Application of Bayesian neural network in prediction of stock time series,'' Comput. Eng. Appl., vol. 55, no. 12, pp. 225–229, 2019.

[13] A. M. Rather, A. Agarwal, & V. N. Sastry, ''Recurrent neural network & a hybrid model for prediction of stock returns,'' Expert Syst. Appl., vol. 42, no. 6, pp. 3234–3241, Apr. 2015, doi: 10.1016/j.eswa.2014.12.003.

[14] A. Sherstinsky, ''Fundamentals of recurrent neural network (RNN) & long short-term memory (LSTM) network,'' Phys. D, Nonlinear Phenomena, vol. 404, Mar. 2020, Art. no. 132306, doi: 10.1016/j.physd.2019.132306.

[15] G. Ding & L. Qin, ''Study on prediction of stock price based on associated network model of LSTM,'' Int. J. Mach. Learn. Cybern., vol. 11, no. 6, pp. 1307–1317, Nov. 2019, doi: 10.1007/s13042-019-01041-1.

[16] X. Yan, W. Weihan, & M. Chang, ''Research on financial assets transaction prediction model based on LSTM neural network,'' Neural Comput. Appl., vol. 33, no. 1, pp. 257–270, May 2020, doi: 10.1007/s00521-020- 04992-7.

[17] M. Nabipour, P. Nayyeri, H. Jabani, A. Mosavi, E. Salwana, & S. Shahab, ''Deep learning for stock market prediction,'' Entropy, vol. 22, no. 8, p. 840, Jul. 2020, doi: 10.3390/e22080840.

[18] Z. D. Aksehir & E. Kiliç, ''How towards handle data imbalance & feature selection problems in CNN-based stock price forecasting,'' IEEE Access, vol. 10,

pp. 31297–31305, 2022, doi: 10.1109/ACCESS.2022.3160797.

[19] Y. Ji, A. W. Liew, & L. Yang, ‘‘A novel improved particle swarm optimization among long-short term memory hybrid model for stock indices forecast,’’ IEEE Access, vol. 9, pp. 23660–23671, 2021, doi: 10.1109/ACCESS.2021.3056713.

[20] X. Zeng, J. Cai, C. Liang, & C. Yuan, ‘‘A hybrid model integrating long short-term memory among adaptive genetic algorithm based on individual ranking for stock index prediction,’’ PLoS ONE, vol. 17, no. 8, Aug. 2022, Art. no. e0272637, doi: 10.1371/journal.pone.0272637.

[21] J. Xue & B. Shen, ‘‘A novel swarm intelligence optimization approach: Sparrow search algorithm,’’ Syst. Sci. Control Eng., vol. 8, no. 1, pp. 22–34, Jan. 2020, doi: 10.1080/21642583.2019.1708830.

[22] J. Borade, ‘‘Stock prediction & simulation of trade using support vector regression,’’ Int. J. Res. Eng. Technol., vol. 7, no. 4, pp. 52–57, Apr. 2018, doi: 10.15623/ijret.2018.0704009.

[23] X. Li & P. Tang, ‘‘Stock price prediction based on technical analysis, fundamental analysis & deep learning,’’ Stat. Decis., vol. 38, no. 2, pp. 146–150, 2022, doi: 10.13546/j.cnki.tjyjc.2022.02.029.

[24] J. Heo & J. Y. Yang, ‘‘Stock price prediction based on financial statements using SVM,’’ Int. J. Hybrid Inf. Technol., vol. 9, no. 2, pp. 57–66, Feb. 2016, doi: 10.14257/ijhit.2016.9.2.05.

[25] J. B. De Long, A. Shleifer, L. H. Summers, & R. J. Waldmann, ‘‘Noise trader risk in financial markets,’’ J. Political Economy, vol. 98, no. 4, pp. 703–738, Aug. 1990, doi: 10.1086/261703.

[26] H. Cui & Y. Zhang, ‘‘Does investor sentiment affect stock price crash risk?’’ Appl. Econ. Lett., vol. 27, no. 7, pp. 564–568, Jul. 2019, doi: 10.1080/13504851.2019.1643448.

[27] R. P. Schumaker, Y. Zhang, C.-N. Huang, & H. Chen, ‘‘Evaluating sentiment in financial news articles,’’ Decis. Support Syst., vol. 53, no. 3, pp. 458–464, Jun. 2012, doi: 10.1016/j.dss.2012.03.001.

[28] M. Nofer & O. Hinz, ‘‘Using Twitter towards predict stock market,’’ Bus. Inf. Syst. Eng., vol. 57, no. 4, pp. 229–242, Jun. 2015, doi: 10.1007/s12599- 015-0390-4.

[29] P. Fan, Y. Yang, Z. Zhang, & M. Chen, ‘‘The relationship between individual stock investor sentiment & stock yield-based on perspective of stock evaluation information,’’ Math. Pract. Theory, vol. 51, no. 16, pp. 305–320, 2021.

[30] Z. Jin, Y. Yang, & Y. Liu, ‘‘Stock closing price prediction based on sentiment analysis & LSTM,’’ Neural Comput. Appl., vol. 32, no. 13, pp. 9713–9729, Sep. 2019, doi: 10.1007/s00521-019-04504-2.

[31] X. Xu & K. Tian, ‘‘A novel financial text sentiment analysis-based approach for stock index prediction,’’ J. Quantum Technol. Econ., vol. 38, no. 12, pp. 124–145, 2021, doi: 10.13653/j.cnki.jqte.2021.12.009.

[32] C.-R. Ko & H.-T. Chang, ‘‘LSTM-based sentiment analysis for stock price forecast,’’ PeerJ Comput. Sci., vol. 7, p. e408, Mar. 2021, doi: 10.7717/peerj-cs.408.

[33] Y. Li & Y. Pan, ‘‘A novel ensemble deep learning model for stock prediction based on stock prices & news,’’ Int. J. Data Sci. Anal., vol. 13, no. 2, pp. 139–149, Sep. 2021, doi: 10.1007/s41060-021-00279-9.

[34] C. Kearney & S. Liu, ‘‘Textual sentiment in finance: A survey of methods & models,’’ Int. Rev. Financial Anal., vol. 33, pp. 171–185, May 2014, doi: 10.1016/j.irfa.2014.02.006.

[35] T. Wang & Z. Zhang, ‘‘Research on construction method of emotional lexicon for movie review,’’ Comput. Digit. Eng., vol. 50, no. 4, pp. 843–848, 2022, doi: 10.3969/j.issn.1672-9722.2022.04.031.

[36] Y. Rao, J. Lei, L. Wenyin, Q. Li, & M. Chen, ‘‘Building emotional dictionary for sentiment analysis of online news,’’ World Wide Web, vol. 17, no. 4, pp. 723–742, Jun. 2013, doi: 10.1007/s11280-013-0221-9.

[37] L. Yang & T. Zhai, ‘‘Research on sentiment tendency analysis of video reviews based on sentiment dictionary,’’ Netw. Secur. Technol. Appl., vol. 255, no. 3, pp. 53–56, 2022.

[38] A. Fathy, T. M. Alanazi, H. Rezk, & D. Yousri, ‘‘Optimal energy management of micro-grid using sparrow search algorithm,’’ Energy Rep., vol. 8, pp. 758–773, Nov. 2022, doi: 10.1016/j.egyr.2021.12.022.

[39] Y. Chen, Z. Liu, C. Xu, X. Zhao, L. Pang, K. Li, & Y. Shi, ‘‘Heavy metal content prediction based on random forest & sparrow search algorithm,’’ J. Chemometrics, vol. 36, no. 10, Sep. 2022, Art. no. e3445, doi: 10.1002/cem.3445.

[40] S. Hochreiter & J. Schmidhuber, ‘‘Long short-term memory,’’ Neural Comput., vol. 9, no. 8, pp. 1735–1780, Nov. 1997, doi: 10.1162/neco.1997.9.8.1735.