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A novel deep learning model for stock market prediction using a sentiment analysis system from authoritative financial website's data

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ABSTRACT

The use of deep learning, specifically time series neural networks, in predicting stock market trends has emerged as a significant use case in financial analysis. However, the complex interrelationships and instability of the stock market have made the timely and accurate prediction of its behaviour as a confronting endeavour. To address this difficulty, in this research work a stock market index prediction model called SenT-In, which combines the with a sentiment awareness model. A sentiment awareness model using Convolutional Neural Networks (CNN) and Gated Recurrent Unit (GRU) is proposed to calculate the sentiment index of a large volume of news articles collected from reputable financial websites. In addition, a sentiment attention method is developed to combine stock data and news sentiment index as the input for training and predicting using the SenT-In network, which is both simple and efficient. The proposed model is evaluated in four different stock market datasets which include FSTE, SSE, Nifty 50 and S&P 500. On comparing the results with conventional deep learning algorithms such as GRU, LSTM, CNN and SVM, proposed SenT-In outperforms existing methods in accuracy with 9%, F1-Score with 7%, AUC-ROC curve with 13% and PR-AUC curve with 9% efficiency (on average).

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KEYWORDS
Informer model; sentiment awareness model; GRU; CNN; Stock market price prediction

1. Introduction

In the past decade, traditional approaches such as fundamental and technical analysis have been used for a considerable amount of time to forecast the stock market. On the other hand, these methods often fall short of adequately capturing the multifaceted and ever-changing character of the market (Lu et al., 2021). The use of sentiment research as a viable alternative for projecting stock prices has been more popular over the last several years (Zhang, Wang, et al., 2018). The potential of sentiment analysis has been proved, especially during significant market events, via the use of data that is rich in sentiment from sources such as social media, news outlets, and other platforms. According to the researcher's community, the phrase "A Sentiment Analysis Approach to the Prediction of Market Volatility" (Deveikyte et al., 2022) has shed light on the fact that there is a link between market

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sentiment and changes in stock prices. However, its efficacy as a standalone tool is still limited, particularly when it comes to forecasting the market returns for the next day. As a result of its limited predictive potential when considered in isolation, the connection between sentiment and returns is often weak and inconsistently statistically significant across a variety of data sources.

The internet is a good platform for evaluating public mood since it is abundant with views and continues to expand in user interaction (Shayaa et al., 2018). This results on the internet serving as a beneficial platform. The internet, especially via online and social media platforms, creates huge volumes of data that represent popular opinions. This contrasts with older techniques or personal networks, which fail to generate such quantity. As a result of the flood of big data from internet platforms and social media platforms, the area of big data analytics has been presented with new employment prospects. According to Ghani et al. (2019), data from social media platforms may be explored via the use of both sophisticated machine learning algorithms and more conventional data mining methods. Data mining techniques are the prime source to get relevant insights from the data collected from social media platforms for sentiment analysis.

On analysing the data from social media platforms, one of the most significant issues that researchers encounter is the enormous amount of data, the presence of noise, and the data's ever-changing nature. However, data mining methods assist overcome these challenges by allowing the extraction of useful insights that may otherwise be unavailable (Barber et al., 2012). This might be a significant advantage in the long run. It is possible to analyse the sentiment that is conveyed in material that is shared on social media by making use of a lexicon of terminology related to sentiment. To anticipate market patterns such as direction, volatility, and trading volume, this sentimental research provides an indicator of the general public's mood, which may be of great use (Checkley et al., 2017).

According to Bollen et al. (2011) and Nofsinger (2005), behavioural finance provides more evidence that supports the relationship between sentiment and financial choices. This provides further evidence that highlights the considerable effect that emotions and mood have on market behaviour. At the same time as the stock market is unquestionably influenced by the news, the emotional reactions of people also play a significant part in determining the movements of the market. With social media, researchers are able to better forecast market trends and behaviours by gaining a knowledge of and gathering information on public attitudes.

Despite the fact that a significant portion of the previous research has concentrated on analysing sentiment from social media data and making use of current sentiment dictionaries, there is an increasing need for a more complete approach that incorporates other factors and data sources. Furthermore, there have been a few studies that have investigated the possibility of merging sentiment research with technical analysis, which is a technique that has been shown to efficiently detect patterns and trends in the stock market (Bhargava & Rao, 2018; Chandrasekaran et al., 2021, 2022). There is continuous research that aims to improve the use of sentiment analysis in stock market forecasting. Sentiment analysis continues to play an important role in determining how the public feels about the equity market. The motivation factors for this research work are listed as follows (1) Stock markets are highly dynamic, exhibiting complex nonlinear patterns that traditional statistical methods struggle to capture. (2) Existing methods often fail to fully leverage the impact of financial sentiment on market movements. Sentiments expressed in authoritative financial platforms hold valuable predictive signals that are underutilised in many models. (3) Market and sentiment data often contain noise and irrelevant features that hinder prediction accuracy. (4) Many deep learning methods, while powerful, struggle with overfitting due to limited training data or inappropriate architecture design. (5) Sentiment analysis and numerical market data often need to be integrated seamlessly, which many models fail to achieve effectively.

In this research work deep learning methods such as CNN, GRU and Informer (Transformer approach) are used to predict the stock market prices using sentiment analysis. The contribution of this research work are as follows:

- Developed a hybrid model, SenT-In, that combines sentiment analysis from financial news with stock market data for improved prediction accuracy.
- Introduced a sentiment analysis framework based on GRU and CNN to derive sentiment indices from a large corpus of financial news collected from authoritative sources.
- Designed a unique sentiment-aware model to effectively fuse stock market data with sentiment indices, enhancing the predictive power of the model.
- Adapted Informer, a time series neural network, for stock market prediction tasks, demonstrating its efficiency and simplicity in handling complex temporal relationships.

The proposed approach offers significant advantages through its innovative hybrid model, SenT-In, which combines sentiment analysis from financial news with numerical stock market data to achieve improved prediction accuracy. Leveraging a GRU-CNN-based sentiment analysis framework, the model derives high-quality sentiment indices from a large corpus of authoritative financial news, preserving temporal context and identifying critical textual patterns. Additionally, the sentiment-aware design effectively fuses stock market data with sentiment indices, capturing interactions between quantitative and qualitative factors for enhanced predictive power. By adapting Informer, a state-of-the-art time-series neural network, the model efficiently handles complex temporal relationships inherent in stock market dynamics, demonstrating both simplicity and robustness. These advancements collectively establish the model as a powerful and comprehensive tool for stock market prediction. Further structure of the article includes related works, background information, proposed methodology, experimental analysis and conclusion.

2. Literature survey

In Malagrino et al. (2018), Malagrino and associates investigated the use of Bayesian networks for the purpose of anticipating daily changes in the Dow Jones Industrial Average index. The results of their research brought to light the advantages of Bayesian networks, such as their capacity to describe complex interactions between variables. The model, on the other hand, had difficulties with real-time analysis delays, which our improved model overcomes by including instantaneous sentiment analysis. This enhancement guarantees that forecasts are both timely and sensitive to shifts in market sentiment throughout the forecasting process. In the study, Shah et al. (2018) built a system that utilises machine learning and statistical approaches to analyse news sentiment and anticipate its impact on stock prices. The system achieved an accuracy rate of 57.14% on the New York Stock

Exchange. While this approach does show some potential, it does have certain limits in terms of accuracy and the selection of sources that are relevant to the story.

In the year 2015, Wu et al. (2014) conducted a study of sentiment analysis in online stock forums and suggested a method that combines techniques such as opinion mining, visualisation, and sentiment analysis. The system achieved an accuracy of 78.5% when it came to predicting sentiment. Their approach, on the other hand, is only dependent on sentiment and does not consider any past data, which may occasionally result in findings that are difficult to interpret. Support vector classifiers, logistic regression, and XGB classifiers were used by Lavanya and Gnanasekaran (2023) to conduct an analysis of the National Stock Exchange. An accuracy rate of 99% was achieved by the XGB classifier, which was the most successful solution. Their study does not take into consideration the wide variety of sectors and commodities that are available on the market, even though these findings are encouraging.

Stock market forecasting discussed by Deepa and Daisy (2023), brought together the fundamental and technical analysis using machine learning. To improve the accuracy of stock predictions, their technology analyses training news data and material from web sources. On the other hand, their method does not include real-time sentiment analysis, which is an essential component in predicting stock prices. Chaudhary et al. (2023) preprocessed data from the stock market using supervised machine learning methods such as KNN and random forest. Their demonstration yields good results in terms of accuracy, recall, and F-measure. On the other hand, our reinforced model significantly outperforms these findings in terms of both accuracy and precision.

Deep learning was used with preprocessing methods by Bhatt et al. (2023) to increase the accuracy of stock prediction. The optimisation of stock functions was the primary emphasis of their model; nevertheless, it was unable to successfully assimilate and incorporate real-time market sentiment. The study conducted by Deswal and Kumar (2023) examined a few different prediction techniques, including as sentiment analysis and machine learning, and highlighted the advantages and disadvantages of each of these approaches. Although these approaches show promise, more development in natural language processing and the incorporation of a wide variety of data sources is still required in order to improve forecasts.

Emphasising the usefulness of social media data for forecasting, He et al. (2016) investigated the association between data from Twitter and stock prices in the financial services industry. Authors Zhang, Cui, et al. (2018) presented a system that used a number of different machine learning algorithms and feature selection strategies. Overall, the system achieved an accuracy of 63.9%, which was higher than the accuracy of benchmark models. Nevertheless, there is a need for more enhancements in the selection of features and the integration of data. On the other hand the applications of machine learning and deep learning are high in number on the sensitive data in the domains such as medical streams (Nazari et al., 2024; Saberi et al., 2024; Sadr et al., 2024), pattern recognition (Amiri et al., 2023; Amiri, Heidari, Jafari, et al., 2024, Amiri, Heidari, Navimipour, et al., 2024) cyber security related problems (Amiri, Heidari, Jafari, et al., 2024, Amiri, Heidari, Navimipour, et al., 2024; Amiri et al., 2023; Heidari, Amiri, Jamali, & Jafari, 2024; Heidari, Amiri, Jamali, & Navimipour, 2024) and so on.

The research that is currently available highlights the potential of sentiment analysis and data from social media platforms in the context of financial market forecasting. The results of this research suggest that social media platforms, and Twitter in particular, provide vital additional data that may be used to make forecasts about the stock market performance. In this research work, incorporates sentiment analysis and technical analysis into a coherent framework, in contrast to earlier studies that mostly focused on examining both approaches in isolation from one another. With sentiment analysis and technical analysis, this method can capture both the emotional components of investor behaviour and the quantitative market dynamics. As a result, it provides a complete tool for improving stock market predictions.

3. Background

This section comprises of the required background knowledge on NLP and deep learning techniques. This section comprises of the word embedding model used for converting individual words into numerical vectors and the next subsection discusses on ProbSparse Attention mechanism which is used as an attention mechanism in the proposed work.

3.1. Word embedding

Word embedding refers to a method used in natural language processing (NLP) that involves converting individual words into a numerical vector. One popular kind of word embedding is Word2vec. It learns word connections from a big corpus of text using a model of a neural network. A trained model like this may either identify terms that are synonymous or provide word suggestions for incomplete sentences.

Continuous Bag of Words (CBOW) and Ship-gram are the two primary models in the word2vec framework. By analysing all nearby words, the CBOW model learns to anticipate a target term. Figure 1 shows that the CBOW model takes the context vectors and averages them. In contrast to the CBOW model, the skip-gram model uses word context to make predictions. Since CBOW only needs to train one SoftMax, it trains quicker than skip-gram. In addition, CBOW works better with words that appear often since it has more training words to work with when a word appears frequently. CBOW can be used easily to solve than skip-gram because, instead of having to guess multiple context words, all it must is to forecast the focal word. As a result, this paper's fundamental training word vector is the CBOW model (Figure 2).

With a word count C and a word vector space size V, the input layer contains the one-hot encoded input context. The output layer is the one-hot encoded word y, while the hidden layers with vectors of N dimensions. The hidden layer is linked to the output layer by a $V \times N$ dimensional weight matrix W, and the one-hot encoded input vector is linked to it through an identical connection.

3.2. Informer model

Informer (Figure 3) is an advanced deep learning model designed for long-term time series forecasting, tackling the computational inefficiencies and scalability issues associated with conventional Transformer models. In contrast to conventional Transformers, which experience quadratic temporal complexity in self-attention processes, Informer use a ProbSparse Attention mechanism. This method preferentially targets the most essential enquiries according to their sparsity in the attention distribution. This transformer model "Informer" integrates a distillation technique to progressively downsample input

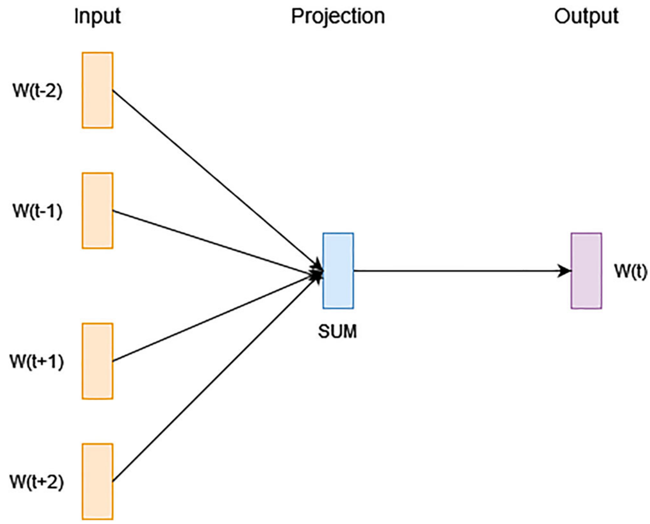


Figure 1. CBOW skeleton.

sequences, eliminating unnecessary information while preserving essential patterns, hence improving efficiency and prediction accuracy.

This model employs an encoder–decoder architecture to interpret time series data by integrating temporal and feature information between attention layers. The encoder uses ProbSparse Attention to capture global dependencies in the input data, whilst the decoder reconstructs and forecasts future values by integrating previous data with acquired attention weights. This integration enables Informer to effectively capture both local and long-term trends in time series data. The use of a learnable positional encoding guarantees the preservation of temporal dependencies during attention calculation, rendering Informer appropriate for high-dimensional sequence processing applications.

Encoder: The encoder processes input sequences X by applying a series of self-attention and feedforward layers. ProbSparse Attention selects only the top-k queries with the largest attention scores:

$$Attention(Q, K, V) = softmax\left(\frac{(QK^T)}{\sqrt{d_k}}\right)V \tag{1}$$

Here, Q, K, and $V$are the query, key, and value matrices derived from H, and d_k is the dimension of the keys.

In ProbSparse Attention, only top-k scores are retained, reducing computational complexity. The encoder output Z_e is given by:

$$Z_e = LayerNorm(X + Attention(Q, K, V))Z_e \tag{2}$$

Decoder: The decoder combines the encoder output Z_e with the past input sequence Y. A cross-attention layer aligns the decoder queries Q_d with the encoder keys $K_{\boldsymbol{e}}$ and values V_e:

$$Cross - Attention(Q_d, K_e, V_e) = softmax\left(\frac{(Q_d K_{e^T})}{\sqrt{d_k}}\right)V_e \tag{3}$$

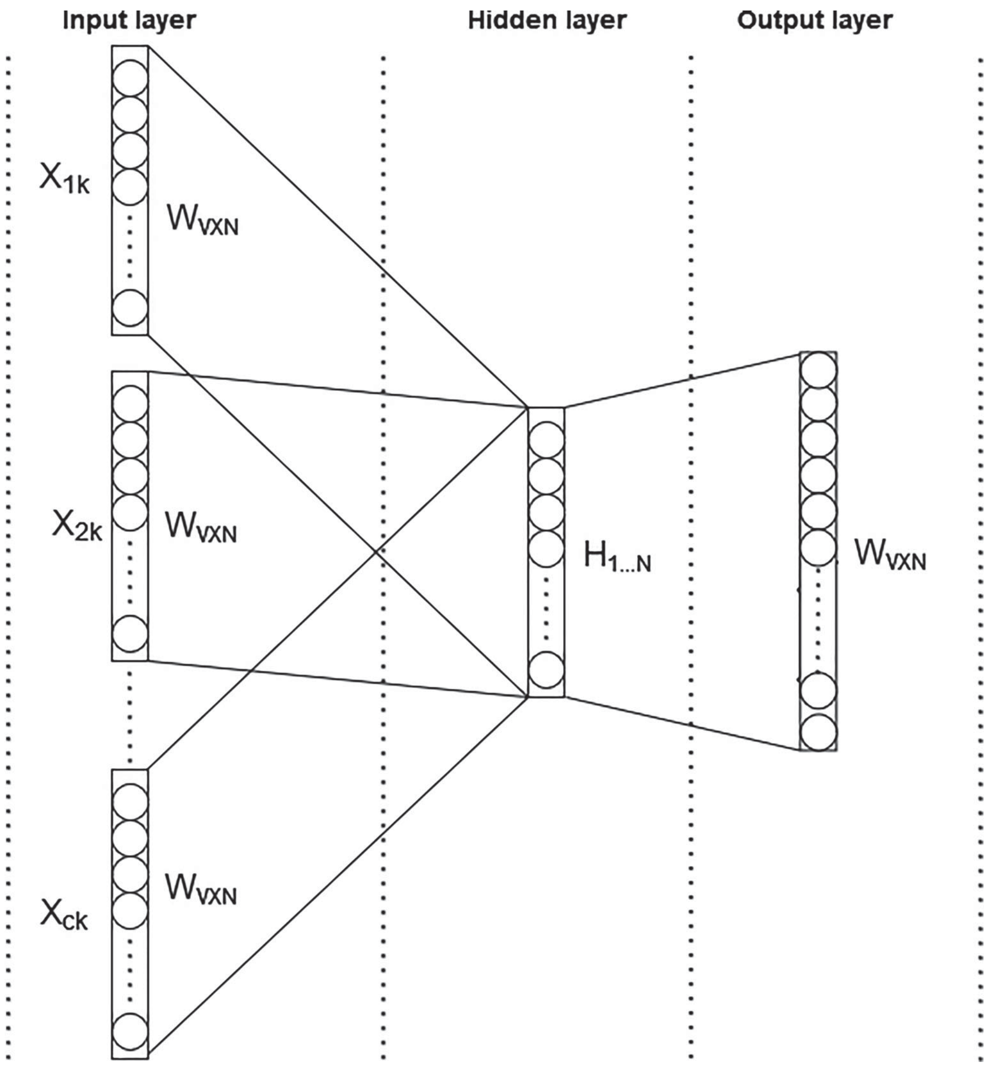


Figure 2. CBWO architecture.

The decoder output $Z_d$is computed as:

$$Z_d = LayerNorm(Y + Cross - Attention(Q_d, K_e, V_e)) \tag{4}$$

The prediction is generated as:

$$\hat{y} = Linear(Z_d) \tag{5}$$

4. Prediction framework

The four main phases of the SenT-In architecture that is proposed in this research for predicting stock market indices are as follows:

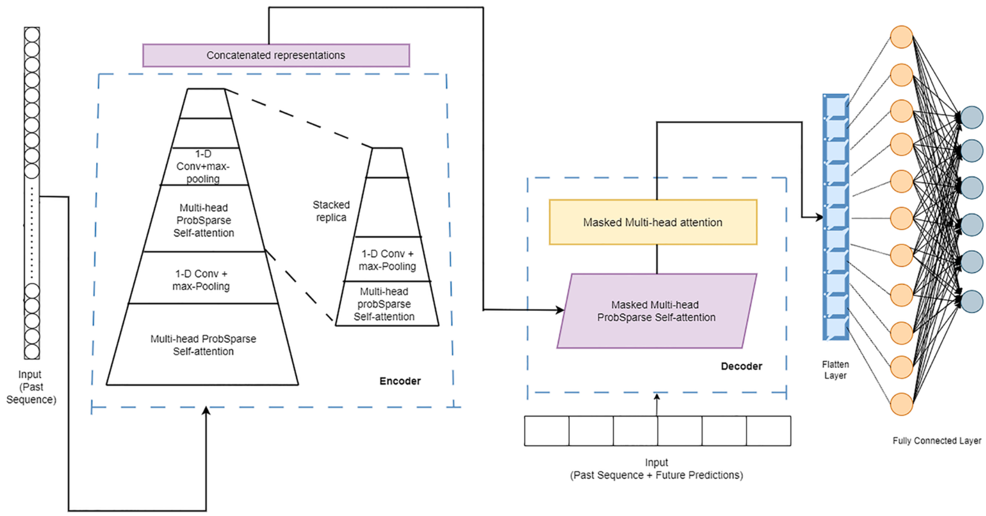


Figure 3. Informer model.

4.1. Sentiment analysis phase

The data (i.e. news) for this section is sourced from the website "investing". The authors employ crawlers to systematically scan and extract data from the "investing" website at regular intervals (3 min cycle), subsequently categorising the gathered news by stock index prior to its storage. Prior to being stored in the database, the authors conducted a comparison to ascertain whether this news is already present. Furthermore, the sentiment index of the acquired news is evaluated using the pre-trained GRU-CNN model.

4.2. Data processing phase

Yahoo Finance is used for the monetary data, namely the daily price history. Low separability of stock market index price information is a consequence of the data's features of duplicated information, noise, and inconspicuous speech. Data normalisation and data cleansing are the two primary components. To remove anomaly values from stock data, cleaning or padding the original data is necessary. Secondly, to ensure that all data are on the same scale, it is necessary to normalise the stock data and sentiment index by removing quantiles from the various datasets.

4.3. Fusion phase

The sentiment index is produced from the values of daily news (average), and the authors feed this into the SenT-In together with the collected stock price feature data.

4.4. Sentiment-aware model

Data fusion is followed by the calculation of each element's awareness weight using the Sentiment-Aware Model from Section 4.6. The resulting data are then weighted to account

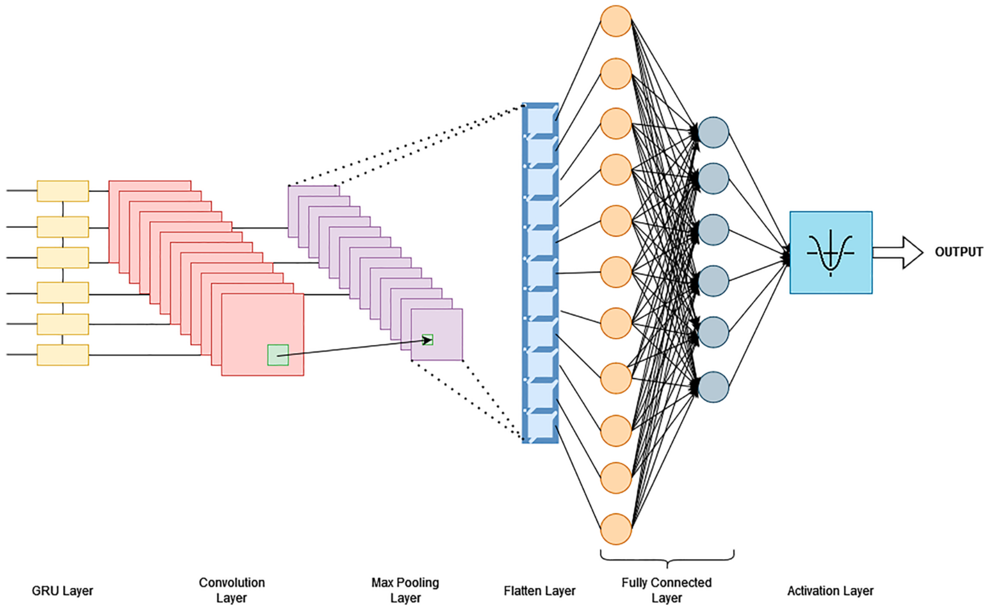


Figure 4. GRU-CNN architecture.

for each element's awareness weight. The next step is to feed the Informer model the weighted data.

4.5. Stock news-based sentiment analysis

The sentiment analysis model combining GRU and CNN can be divided into three main stages: text vectorisation, extraction of features, and sentiment classification. In the first step, the text vocabulary is converted into vector form following the preprocessing approach outlined in Section 3.1 of this study. During feature extraction, the word vectors are re-encoded using GRU, leveraging its robust capability to process sequential data and capture rich contextual information. Subsequently, CNN is applied to these re-encoded vectors to extract fine-grained local semantic features (Figure 4). Finally, sentiment classification is performed using a SoftMax classifier to determine the sentiment orientation of the news content.

The process begins with matrix M that represents textual information into the GRU, resulting in the GRU's output $O_{\lambda \times 1} = [o_1, o_2, \ldots, o_l]$, where λ represents the number of GRU neurons. Next, the output O serves as input to the CNN. In the convolution layer, the width of the convolution kernel matches the number of GRU units, and sliding sampling is performed along the GRU output dimension to obtain $N = [n_1, n_2, \ldots, n_k]$. After processing through the pooling layer, the result is $H = [h_1, h_2, \ldots, h_k]$ with each vector in H flattened into F. In the fully connected layer, a dot product operation is performed between F and W_F, followed by a softmax operation to calculate the final probability for text sentiment classification.

The cross-entropy loss function to be minimised is devised as follows:

$$L = -\sum_{i=1}^{N}\sum_{j=1}^{m}[1\{t_i - j\}\log(y_j)] \tag{6}$$

where N denotes the sample count for training, y represents the predicted probability, and the objective of training is to minimise L.

4.6. Sentiment awareness model

To effectively capture pertinent information, it is essential to understand the importance of each input feature derived from the history of stock market prices. This facilitates the allocation of varying weights to the input features, reflecting their respective significance. The input features are evaluated through the awareness model thereby those features exerting a more significant influence on stock price will be assigned greater weights. To assess the significance of features, a coefficient representing the distribution of awareness serves as the weight parameter. However, it is inappropriate to directly implement the awareness model in the framework, as stock data must fluctuate in accordance with varying sentiment indices.

Thus, a sentiment awareness model is crafted to genuinely elucidate the connection between data and sentiment indices, adhering to the dual structures of data. The model input is composed of two distinct elements: the first element includes stock data along with a corresponding news sentiment index, whereas the second element is exclusively the sentiment index itself. Within this set, $\{e_1, e_2, \ldots, e_N\}, e_{si}$ denotes the embedding vector corresponding to stock data, as well as the embedding vector associated with the sentiment index, respectively. The output of the activation unit is represented as $\{w_1, w_2, \ldots, w_N\}$, which is derived from the inputs $\{e_1, e_2, \ldots, e_N\}$ ande_{si}. Additionally, w_{si} denotes the output of another activation unit that takes e_{si} and e_{si}as its inputs.

4.7. SenT-In model for prediction

The stock market index data $x_1, x_2, \ldots, x_t$ are used to forecast the closing prices $y_1, y_2, \ldots, y_t$. The trend in the stock price may therefore be seen as a time series because of this. The grid network architecture takes use of both CNN and GRU merging their strengths. Hence, it outperforms state-of-the-art CNN, GRU, and self-attention models on multinomial sequence modelling challenges. The authors present a grid network that is built on sentiment-aware as a means of capturing linkages within stock sequences. Figuring out the SenT-In model's design is shown in Figure 5.

An input layer, an Informer network layer, a fully connected layer, a sentiment index aware mechanism layer, and an output layer are the components of SenT-In model. The dataset needed to train the model is first processed and normalised by the input layer. Figure 6 shows the overall flow of the proposed work. The sentiment-aware technique, detailed in Section 4.6, is then applied to the preprocessed data in order to derive weights for each element and extract deep features. As a result, the sequence is weighted according to the importance of each component. This is followed by feeding the Informer network the weighted sequence. Further, a completely linked layer converts the feature space of the

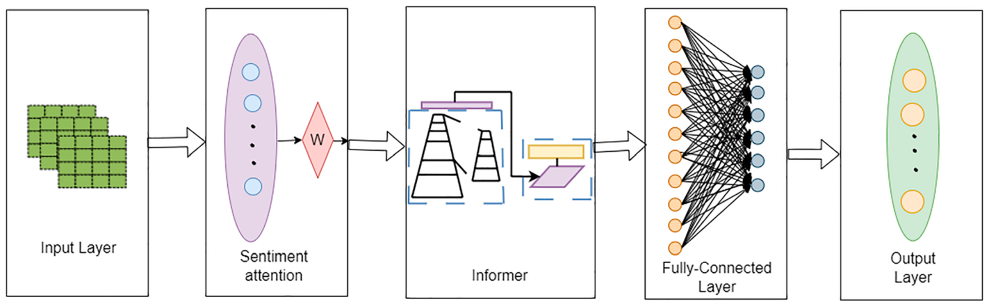


Figure 5. SenT-In model.

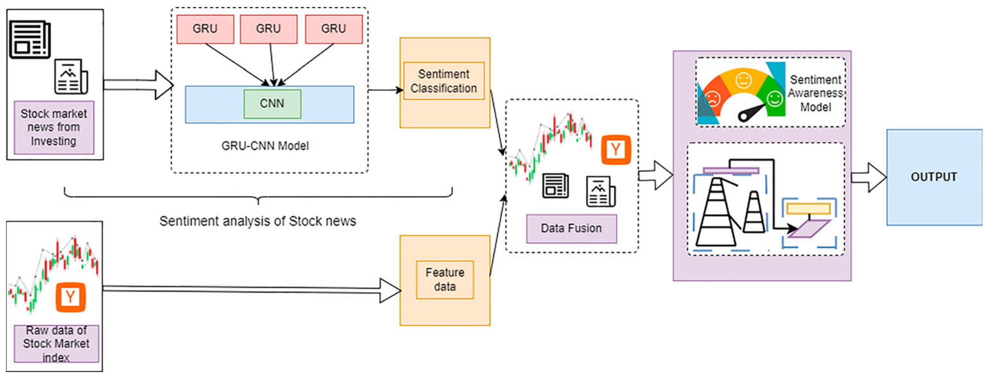


Figure 6. Architecture of prediction framework.

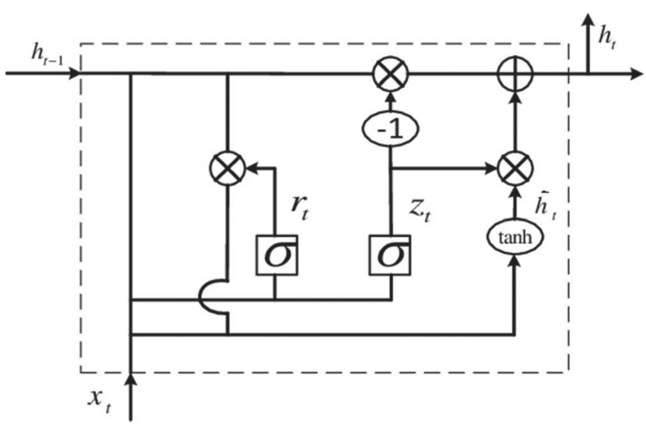


Figure 7. GRU model.

preceding layer into a label space for the sample. The Informer model makes use of GRU as the nonlinear activation function and it shows effectiveness in recurrent networks, as shown in Figure 7.

The GRU processes the raw time-series input X to extract sequential features. The GRU cell is defined as follows:

$$z_t = \sigma(W_z X_t + U_z h_{\{t-1\}} + b_z) \tag{7}$$

$$r_t = \sigma(W_r X_t + U_r h_{\{t-1\}} + b_r) \tag{8}$$

$$\tilde{h}_t = tanh(W_h X_t + U_h(r_t \odot h_{\{t-1\}}) + b_h) \tag{9}$$

$$h_t = z_t \odot h_{\{t-1\}} + (1 - z_t) \odot \tilde{h}_t \tag{10}$$

where X_t is the input at time step t, h_t is the hidden state, σ and $tanh$ are activation functions, and $W_z, W_r, W_h, U_z, U_r, U_h, b_z, b_r, b_h$ are learnable parameters.

The GRU processes the sequence $X = \{X_1, X_2, \ldots, X_T\}$ and produces a sequence of hidden states $H = \{h_1, h_2, \ldots, h_T\}$:

$$H = GRU(X) \tag{11}$$

The choice of Informer is justified by its superior ability to handle long-sequence dependencies efficiently, which is essential for financial data characterised by temporal complexity and the need for capturing long-term trends. Unlike traditional models like LSTMs, which struggle with vanishing gradient issues when dealing with long sequences, Informer utilises a sparse attention mechanism that selectively focuses on the most relevant parts of the input sequence, significantly improving computational efficiency and scalability.

Moreover, while Transformers have demonstrated powerful capabilities for sequence modelling, their quadratic complexity with respect to input sequence length poses practical challenges when processing large-scale financial datasets. Informer's design addresses this limitation by employing a self-attention mechanism optimised for long sequences, maintaining a balance between accuracy and computational efficiency. This makes it particularly well-suited for the high-dimensional, time-sensitive nature of stock market prediction tasks.

The comparative analysis highlights that while LSTMs are effective for shorter sequences and Transformers excel in many domains, Informer's sparse attention mechanism and adaptability to long-sequence scenarios position it as the optimal choice for the proposed model. Its ability to model both global trends and local variations with reduced computational overhead further validates its selection.

5. Experimental analysis

The proposed model is implemented in Python Version 3.7 on the computational system with specifications of processor Intel Core i7 12th generation with clock speed 3.2 GHz of 16GB RAM and 512 GB SSD. In this section the dataset used for evaluation of the proposed model is described along with the experimental setup and the result analysis.

5.1. Dataset description

The dataset must be collected in two aspects: Numerical stock market price data and sentiment tag. As discussed in Section 3, the sentiment tags are generated for every day of the stock market for the considered datasets. A total of four datasets are considered and they are tabulated in Table 1. A total of 6298 data are being analysed between January 1, 2005

Table 1. Dataset considered.

Sl. No.	Dataset name	Time period
1	S&P 500	From. January 2005.To. March 2022
2	Financial Times Stock Exchange (FTSE)	
3	Shanghai Stock Exchange (SSE)	
4	Nifty 50 (U.S, U.K, China and India)	

and March 31, 2022. On the holiday's previous date values are filled using data cleaning process.

5.2. *Experimental setup*

To evaluate the sentiment analysis and to evaluate the stock market prediction, the Epoch numbers and other aspects are fixed after an empirical analysis on the proposed model. The simulation parameters are fixed as follows:

5.3. *Result analysis*

The proposed model are experimented on the following aspects: Cross Entropy loss function (Sentiment analysis), Convergence Loss, Convergence Accuracy, F1-Score, AUC-ROC curve and PR-AUC curve.

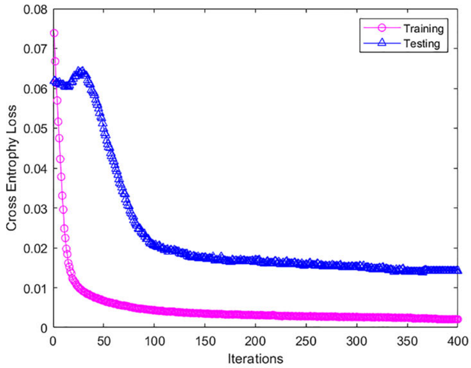
5.3.1. *Cross entropy loss function*

The cross-entropy loss function graphs (Figure 8(a–d)) illustrate the training and testing loss trends for sentiment analysis across four major stock indices: S&P 500, FTSE, SSE, and Nifty 50.

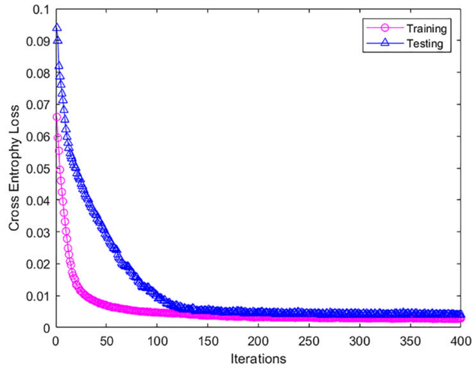
In all cases, the training loss, represented by pink circles, starts at relatively high values (ranging from 0.07 to 0.09) and decreases sharply within the initial iterations, stabilising at minimal values between 0.002 and 0.005. Similarly, the testing loss, represented by blue triangles, begins at slightly lower initial values (between 0.06 and 0.08) and converges to stable levels between 0.007 and 0.01, indicating strong generalisation to unseen data. For the S&P 500 (Figure 8(a)), the testing loss stabilises at 0.01, with a minimal gap from the training loss, reflecting excellent learning. For FTSE (Figure 8(b)), the model shows robust convergence as testing loss reduces to 0.009. SSE (Figure 8(c)) highlights effective model performance, with testing loss stabilising at 0.008 and closely aligned with training loss, showcasing minimal overfitting. Similarly, Nifty 50 (Figure 8(d)) demonstrates strong performance with testing loss stabilising at 0.007. Across all indices, the rapid decline and stabilisation of losses, coupled with minimal gaps between training and testing curves, highlight the model's efficiency in learning patterns and its ability to generalise effectively. This robust performance underscores the model's capability to accurately classify sentiments for stock market prediction, offering reliable insights for decision-making (Tables 2 and 3).

5.3.2. *Prediction analysis of proposed vs existing models*

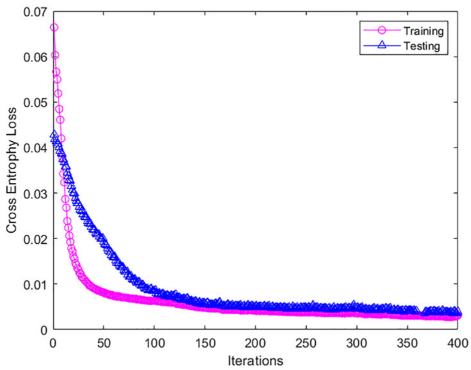
Table 4 shows the experimental results of SenT-In vs existing models on S&P 500 Dataset. Comparing the accuracy of the proposed SenT-In, it outperforms the existing models such



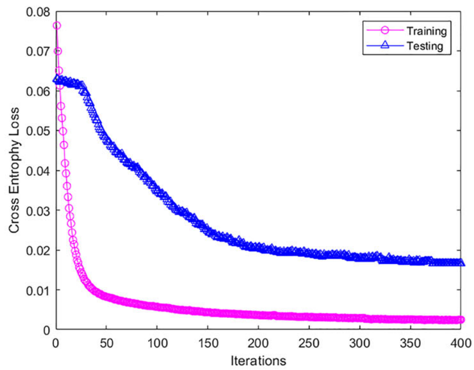
a: Cross entropy loss function on S&P 500



b: Cross entropy loss function on FTSE



c: Cross entropy loss function on SSE



d: Cross entropy loss function on Nifty 50

Figure 8. Cross entropy loss function comparison on training and testing phase. (a) Cross entropy loss function on S&P 500. (b) Cross entropy loss function on FTSE. (c) Cross entropy loss function on SSE. (d) Cross entropy loss function on Nifty 50.

Table 2. Simulation parameters.

Sl. No.	Parameters	Values
1	Epochs for cross entropy loss function	400
2	Epochs for SenT-In evaluation	150
3	training testing ratio	80.20
4	Learning rate	0.01
5	Batch size	16–128
6	Epochs	100
7	Dropout rate	0.1
8	Pool size	2

as SVM with 16.39%, CNN with 5.91%, LSTM with 1.04% and GRU with 12.77%. Comparing the F1-Score of the proposed SenT-In, it outperforms the existing models such as SVM with 8.27%, CNN with 7.53%, LSTM with 2.63% and GRU with 6.38%. Comparing the results of AUC-ROC of the proposed SenT-In, it outperforms the existing models such as SVM with 29.41%, CNN with 15.81%, LSTM with 6.43% and GRU with 12.78%. Comparing the results of PR-AUC of the proposed SenT-In, it outperforms the existing models such as SVM with 15.13%, CNN with 6.58%, LSTM with 7.76% and GRU with 8.73%.

Table 3. Parameters of Informer model.

Sl. No.	Parameter	Typical range
1	Batch size	256
2	Learning rate	1.00E-03
3	Loss function	MSE
4	Optimizer	SGD
5	Epochs	100

Table 4. Experimental results of SenT-In vs existing models on S&*P* 500 Dataset.

Model	Accuracy	F1-Score	AUC-ROC	PR-AUC
SVM	0.6822	0.7498	0.6587	0.8033
CNN	0.7677	0.7558	0.7856	0.8843
LSTM	0.8075	0.7959	0.8731	0.8731
GRU	0.7117	0.7653	0.8139	0.8639
SenT-In	0.8159	0.8174	0.9331	0.9465

Table 5. Experimental results of SenT-In vs existing models on FTSE Dataset.

Model	Accuracy	F1-Score	AUC-ROC	PR-AUC
SVM	0.7811	0.8136	0.7734	0.8466
CNN	0.9160	0.9137	0.9176	0.9534
LSTM	0.9293	0.9341	0.9876	0.9886
GRU	0.8806	0.8928	0.9591	0.9638
SenT-In	0.9579	0.9521	0.9970	0.9963

Table 5 shows the experimental results of SenT-In vs existing models on FTSE Dataset. Comparing the accuracy of the proposed SenT-In, it outperforms the existing models such as SVM with 18.46%, CNN with 4.38%, LSTM with 2.99% and GRU with 8.07%. Comparing the F1-Score of the proposed SenT-In, it outperforms the existing models such as SVM with 14.55%, CNN with 4.03%, LSTM 1.89% and GRU with 6.22%. Comparing the results of AUC-ROC of the proposed SenT-In, it outperforms the existing models such as SVM with 22.42%, CNN with 7.96%, LSTM with 0.94% and GRU with 3.8%. Comparing the results of PR-AUC of the proposed SenT-In, it outperforms the existing models such as SVM with 15.03%, CNN with 4.31%, LSTM with 0.78% and GRU with 3.26%.

Table 6 shows the experimental results of SenT-In vs existing models on SSE Dataset. Comparing the accuracy of the proposed SenT-In, it outperforms the existing models such as SVM with 18.21%, CNN with 3.75%, LSTM with 7.24% and GRU with 21%. Comparing the F1-Score of the proposed SenT-In, it outperforms the existing models such as SVM with 16.04%, CNN with 6.6%, LSTM with 0.93% and GRU with 16.19%. Comparing the results of AUC-ROC of proposed SenT-In, it outperforms the existing models such as SVM with 24.84%, CNN with 10.06%, LSTM with 0.93% and GRU with 16.19%. Comparing the results of PR-AUC of proposed SenT-In, it outperforms the existing models such as SVM with 15.93%, CNN with 6.27%, LSTM with 0.67% and GRU with 14.86%.

Table 7 shows the experimental results of SenT-In vs existing models on Nifty 50 Dataset. Comparing the accuracy of the proposed SenT-In, it outperforms the existing models such as SVM with 22.3%, CNN with 2.89%, LSTM with 10.21% and GRU with 25.45%. Comparing the F1-Score of the proposed SenT-In, it outperforms the existing models such as SVM with 18.54%, CNN with 2.26%, LSTM with 5.77% and GRU with 16.78%. Comparing the results

Table 6. Experimental results of SenT-In vs existing models on SSE Dataset.

Model	Accuracy	F1-Score	AUC-ROC	PR-AUC
SVM	0.7173	0.7432	0.7127	0.8043
CNN	0.8441	0.8267	0.8529	0.8967
LSTM	0.8135	0.8193	0.9395	0.9503
GRU	0.6928	0.7523	0.7948	0.8145
SenT-In	0.8770	0.8851	0.9483	0.9567

Table 7. Experimental results of SenT-In vs existing models on Nifty 50 Dataset.

Model	Accuracy	F1-Score	AUC-ROC	PR-AUC
SVM	0.6537	0.6895	0.6491	0.7717
CNN	0.8171	0.8273	0.8420	0.8962
LSTM	0.7555	0.7975	0.7916	0.7888
GRU	0.6273	0.7043	0.6445	0.6480
SenT-In	0.8414	0.8464	0.9212	0.9309

of AUC-ROC of the proposed SenT-In, it outperforms the existing models such as SVM with 29.54%, CNN with 8.6%, LSTM with 14.07% and GRU with 30.03%. Comparing the results of PR-AUC of the proposed SenT-In, it outperforms the existing models such as SVM with 17.1%, CNN with 3.72%, LSTM with 15.27% and GRU with 30.39%.

5.3.3. Convergence loss analysis

The convergence loss analysis for stock market price prediction, shown in Figure 9(a)–(d), emphasises the training and testing loss patterns for the S&P 500, FTSE, SSE, and Nifty 50 indices.

In all instances, the training loss exhibits a consistent decrease, starting at about 0.7 and converging to values between 0.1 and 0.3, signifying the model's proficient acquisition of patterns within the training data. The testing loss has a similar decreasing trend but demonstrates more unpredictability, especially in the first repetitions, indicating the difficulties of generalising to test data. The testing loss for the S&P 500 (Figure 9(a)) and FTSE (Figure 9(b)) stabilises with little swings, indicating strong generalisation. In SSE (Figure 9(c)), the testing loss roughly corresponds with the training loss, demonstrating successful convergence. Conversely, Nifty 50 (Figure 9(d)) demonstrates more pronounced variations in testing loss, indicating potential instability in generalisation for this dataset. The declining trends in both training and testing loss across all indices underscore the model's capacity for convergence, yielding dependable forecasts for stock market price fluctuations.

5.3.4. Convergency accuracy analysis

The convergence study of accuracy for stock market price prediction, shown in Figure 10(a)–(d), emphasises the training and testing accuracy patterns for the key indices: S&P 500, FTSE, SSE, and Nifty 50.

The training accuracy consistently increases throughout all figures, beginning at roughly 55–60% and stabilising around 90% as iterations advance, reflecting the model's capacity to learn patterns from the training data successfully. The testing accuracy exhibits more fluctuation in the first iterations as the model adjusts to unfamiliar data, ultimately converging with the training accuracy and stabilising between 85% and 90% for most indices. In Figure 10(a) (S&P 500) and 10(b) (FTSE), the testing accuracy roughly corresponds with

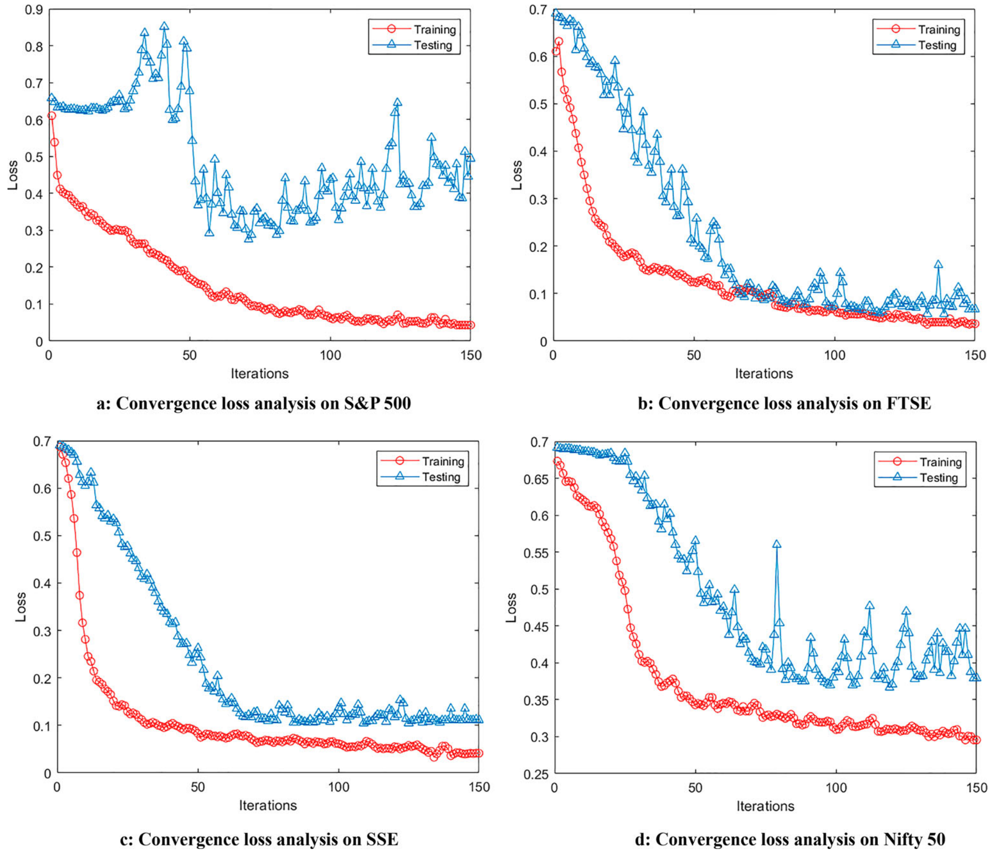


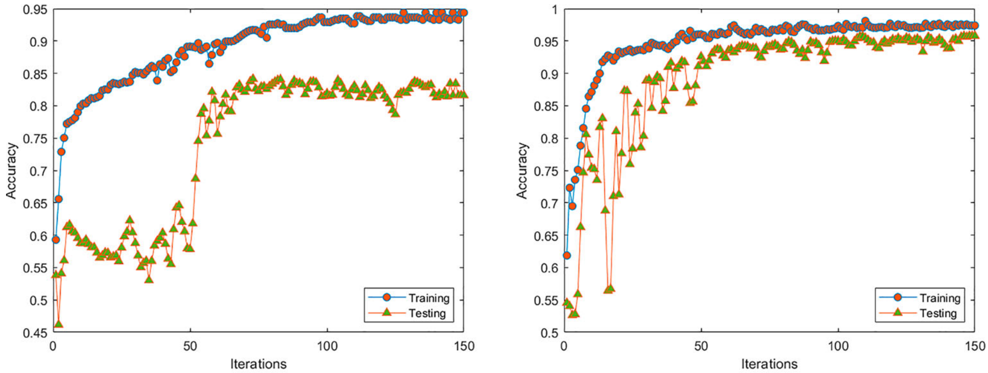
Figure 9. Convergence loss comparison on training and testing phase. (a) Convergence loss analysis on S&P 500. (b) Convergence loss analysis on FTSE. (c) Convergence loss analysis on SSE. (d). Convergence loss analysis on Nifty 50.

the training accuracy in subsequent iterations, indicating strong generalisation. LiSimilarly, Figure 10(c) (SSE) demonstrates consistent performance with a seamless convergence of testing accuracy. Figure 10(d) (Nifty 50) demonstrates somewhat more variability in testing accuracy, indicating a degree of sensitivity to the dataset's attributes. The convergence of accuracy in both training and testing stages across all indices illustrates the model's efficacy in reliably forecasting stock market changes.

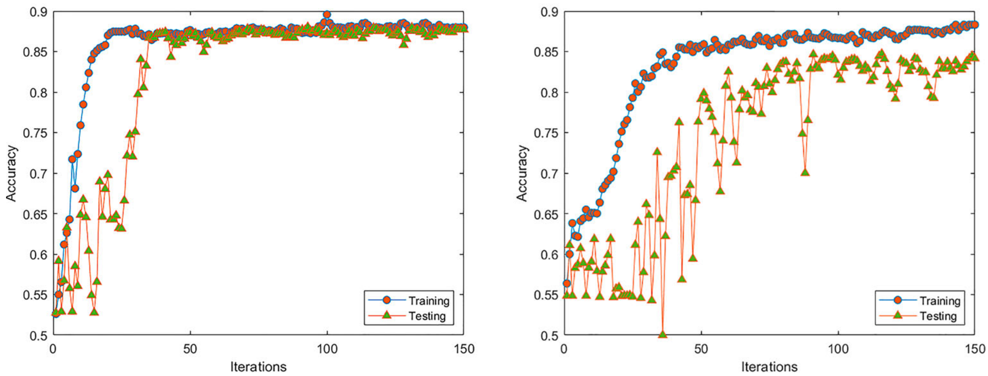
5.3.5. F1-Score analysis

The F1-Score evaluation for stock market price prediction, shown in Figure 11(a)–(d), reveals the training and testing performance for the S&P 500, FTSE, SSE, and Nifty 50 indices.

In all instances, the training F1-Score commences at about 0.7 and exhibits a steady upward trajectory, stabilising at 0.9 after 150 iterations, signifying the model's proficiency in balancing accuracy and recall on the training dataset. The testing F1-Score demonstrates variability in the first iterations as the model adjusts to unfamiliar data, ultimately converging to closely match the training F1-Score, stabilising between 0.85 and 0.9 for most indices. The testing F1-Score for the S&P 500 (Figure 11(a)) and FTSE (Figure 11(b)) has a



a: Convergence analysis of accuracy on S&P 500 **b: Convergence analysis of accuracy on FTSE**



c: Convergence analysis of accuracy on SSE **d: Convergence analysis of accuracy on Nifty 50**

Figure 10. (a) Convergence analysis of accuracy on S&P 500. (b) Convergence analysis of accuracy on FTSE. (c) Convergence analysis of accuracy on SSE. (d) Convergence analysis of accuracy on Nifty 50.

significant correlation with the training F1-Score, indicating solid performance. Likewise, SSE (Figure 11(c)) attains consistent F1-Score convergence, signifying little variation. Conversely, Nifty 50 (Figure 11(d)) exhibits somewhat greater swings in the testing F1-Score, indicating variability in generalisation performance. The F1-Score trends demonstrate the model's proficiency in balancing false positives and false negatives, hence assuring dependable forecasts for stock market price fluctuations across several indices.

5.3.6. AUC-ROC analysis

The AUC-ROC study for stock market price prediction, shown in Figure 12(a)–(d), offers a quantitative assessment of existing models – SVM, CNN, LSTM, GRU, and SenT-In – across the S&P 500, FTSE, SSE, and Nifty 50 indices. Among them, SenT-In attains the greatest performance, with an AUC around 1.0, illustrating its remarkable capacity to differentiate between positive and negative classes. In Figure 12(a) (S&P 500), SenT-In routinely attains a True Positive Rate (TPR) of 0.95, while maintaining a False Positive Rate (FPR) below 0.1, indicating its exceptional sensitivity and specificity. In Figure 12(b) (FTSE) and 12c (SSE), SenT-In consistently exhibits elevated AUC values with little variation, demonstrating its resilience across diverse datasets.

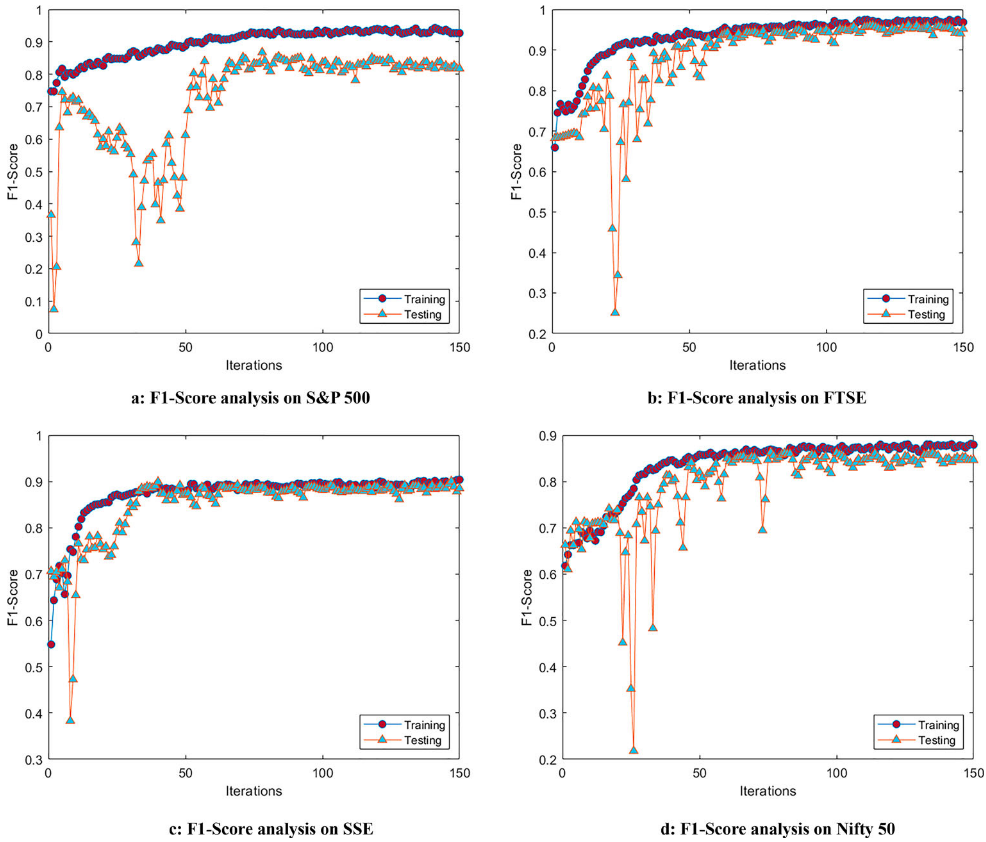


Figure 11. (a) F1-Score analysis on S&P 500. (b). F1-Score analysis on FTSE. (c) F1-Score analysis on SSE. (d) F1-Score analysis on Nifty 50.

GRU and LSTM closely track SenT-In, with AUC values over 0.9 across the majority of datasets. In Figure 12(d) (Nifty 50), the GRU attains a TPR of 0.90 at an FPR of 0.2, demonstrating robust classification performance, but somewhat less accurate than SenT-In. LSTM has comparable performance, with an AUC over 0.85 across all indices, but with a little worse TPR relative to GRU at elevated FPR thresholds. These findings demonstrate that whereas GRU and LSTM provide dependable classification skills, the authors display a worse equilibrium between accuracy and recall relative to SenT-In.

In contrast, CNN demonstrates intermediate performance, with AUC values between 0.75 and 0.85, indicating its ability to generalise across datasets but sometimes compromising accuracy. The SVM has the worst AUC performance, with curves around the diagonal line (AUC 0.6–0.7), indicating classification skills that are just slightly superior than random chance. This underscores the constraints of conventional machine learning methodologies, such as SVM, in sentiment-based stock market forecasting. SenT-In is the most resilient model, constantly achieving high AUC values and providing accurate predictions across all datasets, followed closely by GRU and LSTM, whilst CNN and SVM exhibit worse performance.

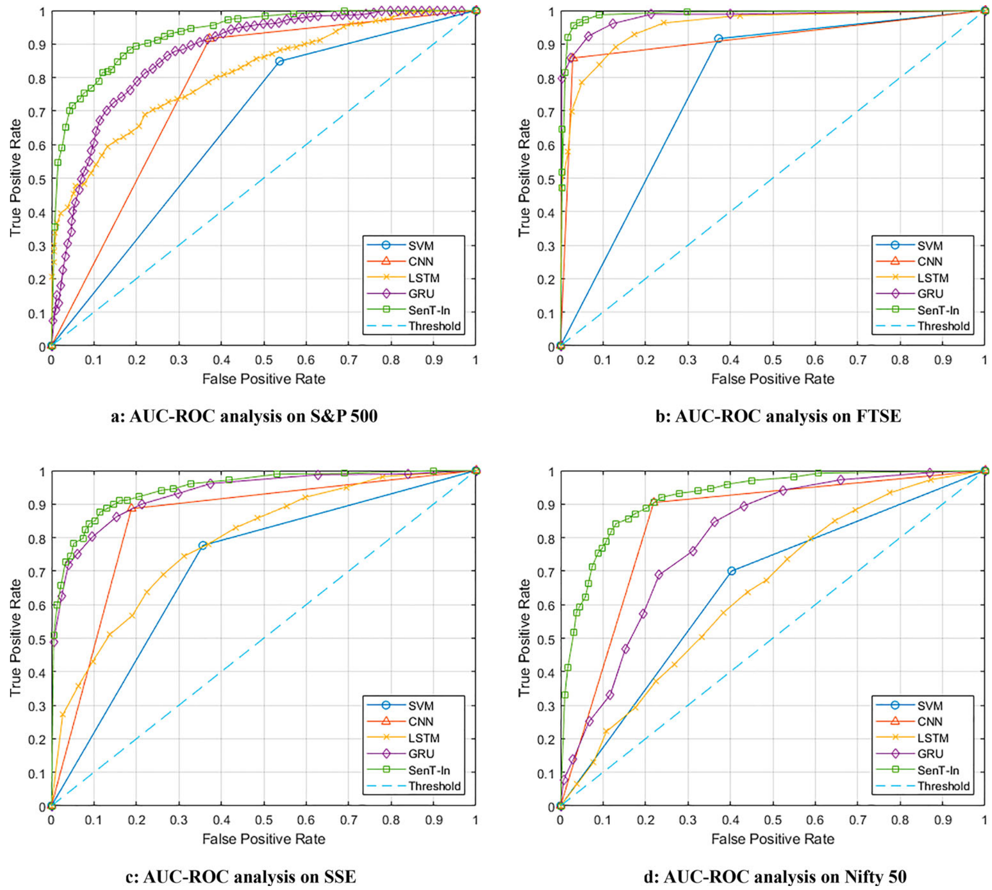


Figure 12. (a) AUC-ROC analysis on S&P 500. (b) AUC-ROC analysis on FTSE. (c) AUC-ROC analysis on SSE. (d) AUC-ROC analysis on Nifty 50.

5.3.7. PR-AUC analysis

The PR-AUC study of stock market price prediction, shown in Figure 13(a)–(d), evaluates the performance of SVM, CNN, LSTM, GRU, and SenT-In models across the S&P 500, FTSE, SSE, and Nifty 50 indices. Among the models, SenT-In consistently attains the optimal balance of accuracy and recall, with a precision above 0.95 at recall levels reaching 0.8 across all datasets. In Figure 13(a) (S&P 500), SenT-In sustains an accuracy above 0.90 throughout a broad spectrum of recall, illustrating its proficiency in managing both false positives and false negatives adeptly. In Figure 13(b) (FTSE) and 13(c) (SSE), SenT-In demonstrates no decline in accuracy at high recall levels, establishing it as the most resilient model for both datasets.

GRU and LSTM rank as the second-best models, with GRU sustaining a precision above 0.85 for recall values ranging from 0.6 to 0.7 before seeing a progressive fall. In Figure 13(d) (Nifty 50), GRU attains a recall of 0.7 and a precision of roughly 0.85, demonstrating good generalisation abilities but inferior robustness relative to SenT-In. CNN shows reasonable performance, achieving a precision of around 0.8 for recall values under 0.5; nevertheless, its accuracy markedly declines as recall rises, signifying its difficulty in sustaining equilibrium at elevated thresholds. The SVM has the worst performance, with accuracy falling below 0.7

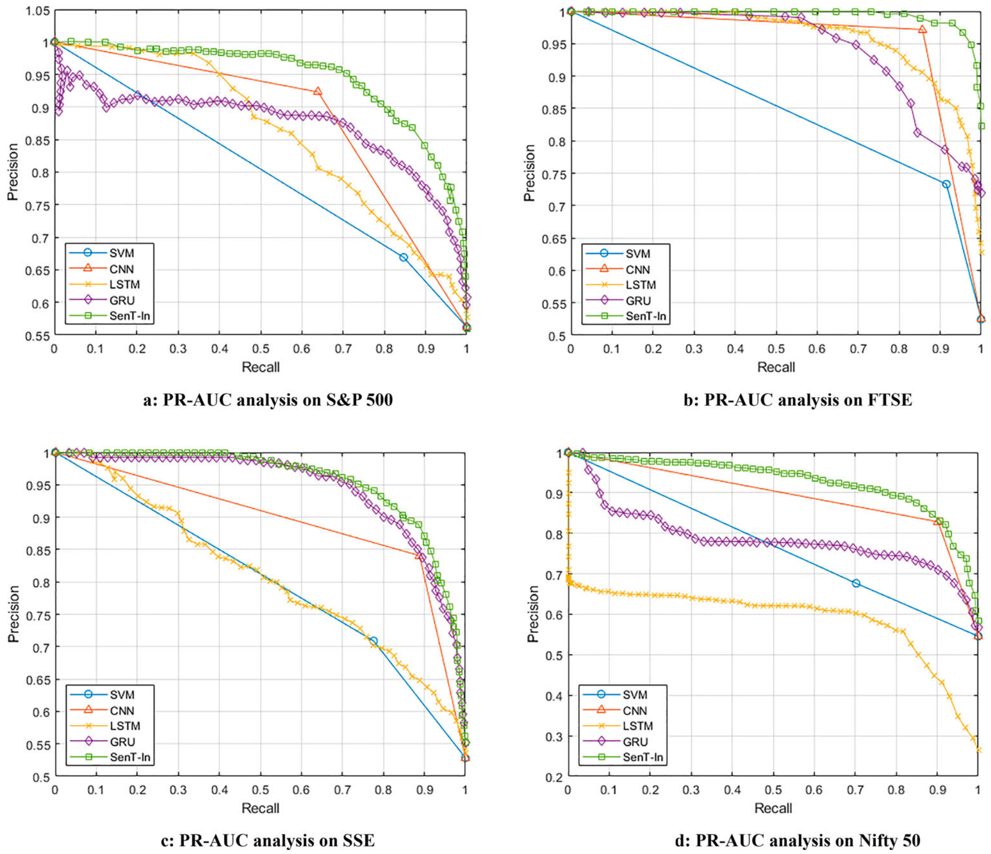


Figure 13. (a) PR-AUC analysis on S&P 500. (b) PR-AUC analysis on FTSE. (c) PR-AUC analysis on SSE. (d) PR-AUC analysis on Nifty 50.

at recall levels as low as 0.4, indicating its limited use for intricate sentiment-driven stock market prediction tasks. The research highlights SenT-In as the most effective model, followed by GRU and LSTM, whilst CNN and SVM fall short owing to their failure to maintain a good precision-recall balance across all datasets.

6. Conclusion

In this research work, the authors introduced SenT-In, a novel deep-learning model for stock market prediction that uses a sentiment-aware technique. The suggested model uses deep learning techniques in conjunction with sentiment analysis from credible financial news sources to address the challenges of predicting the stock market's complex and ever-changing behaviour. To reliably estimate sentiment indices from a variety of financial news sources, the sentiment awareness module utilises CNN and GRU. To build a strong and successful forecasting system, the sentiment attention approach allows for the effective integration of sentiment indices with stock market data. Adapting the proposed SenT-In model to other domains like commodities or cryptocurrency markets can be highly impactful, given the similar dynamics of temporal data and sentiment's role in market movements.

In comparison to more traditional models like GRU, LSTM, CNN, and SVM, the model outperformed the competition after extensive testing on a variety of stock market datasets. Findings from this research show that financial forecasts benefit from using sentiment analysis in conjunction with time series neural networks. SenT-In provides a scalable and cost-effective method for stock market research while simultaneously improving the accuracy of forecasts. The effectiveness and usefulness of the model might be improved in future studies by adding more data sources, such as social media sentiment, incorporating real-time data streams, exploring multilingual sentiment analysis for global markets, and integrating reinforcement learning for adaptive model optimisation.

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