

Deep Learning-Based Sentiment Analysis Using Gated Recurrent Unit

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Abstract— In today's volatile financial markets, investor sentiment plays a crucial role in shaping market dynamics and influencing investment decisions. Traditional analytical methods often fail to capture the subtle emotional cues embedded in vast amounts of unstructured textual data derived from news articles, social media, and financial reports. This study addresses this challenge by employing a deep learning-based approach using Gated Recurrent Units (GRU) for sentiment analysis, thereby enhancing the accuracy of financial market predictions. The research employs a systematic methodology that begins with data collection from various financial sources. This is followed by rigorous preprocessing, including data cleaning, tokenization, and downsampling to balance sentiment classes. Sentiment labeling and feature engineering, utilizing word embeddings, convert textual data into a format suitable for deep learning. The Gated Recurrent Unit (GRU) model is then trained on these features, and its performance is evaluated using metrics such as accuracy, precision, recall, and F1-score. Results indicate that while the Gated Recurrent Unit (GRU) model effectively captures neutral sentiments, it struggles to accurately classify negative and positive sentiments, highlighting areas for improvement. These findings underscore the potential of GRU-based models in financial sentiment analysis while emphasizing the need for refined techniques to enhance classification accuracy. Future research should investigate hybrid architectures, integrate attention mechanisms, and leverage real-time data to enhance the robustness and comprehensiveness of market forecasting. These insights strongly advocate for ongoing advancements in deep learning strategies to refine sentiment classification and financial prediction models.

Keywords: *deep learning, financial markets, GRU, sentiment analysis, stock prediction, text mining.*

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1. Introduction

In recent years, the integration of deep learning techniques with sentiment analysis has garnered significant attention in various fields, particularly in finance. Financial markets are characterized by their inherent volatility, and understanding the underlying sentiments that drive market movements can be invaluable for investors, traders, and analysts [1], [2]. Traditional methods of financial analysis often rely on historical data, technical indicators, and economic reports. However, with the advent of deep learning, there is a growing trend to incorporate alternative sources of information, such as social media, news articles, and financial reports, to forecast market behaviour [3], [4], [5]. Sentiment analysis, the process of determining the sentiment or opinion expressed in text, is one technique that has been increasingly applied to financial data. The primary goal of sentiment analysis in the context of financial markets is to extract insights from textual data to predict market trends, price movements, and other financial outcomes [6], [7], [8], [9]. Sentiment analysis models employ various machine learning algorithms to classify textual data into predefined categories, such as positive, negative, or neutral

sentiment.

Among the various deep learning techniques available for sentiment analysis, Gated Recurrent Units (GRUs) have emerged as a promising architecture. GRUs, a type of recurrent neural network (RNN), have demonstrated superior performance in sequential data processing, especially when dealing with long-range dependencies [10], a common characteristic in financial time series data. Unlike traditional models such as support vector machines (SVMs) or decision trees, GRUs are capable of learning intricate patterns in large volumes of textual data, making them an ideal choice for sentiment analysis tasks. This study explores the use of GRU-based deep learning models for sentiment analysis in financial markets. The primary objective is to analyze textual data from multiple sources such as news articles, social media posts, and financial reports, and use sentiment labels derived from this data to predict stock price movements and market trends. By leveraging deep learning, the study aims to improve the accuracy and efficiency of sentiment analysis, which can be instrumental in making informed financial decisions.

Sentiment analysis, also known as opinion mining, is the computational task of identifying and extracting subjective information from text [11], [12]. The field of sentiment analysis has gained considerable attention in recent years, particularly in the domain of finance, where the impact of public sentiment on market performance is well-documented. Financial markets are heavily influenced by the collective opinions and emotions of investors, which are often reflected in news, reports, and social media [13]. Therefore, analyzing sentiment in financial texts can provide valuable insights into market trends and behavior [14].

A number of studies have demonstrated the effectiveness of sentiment analysis for predicting stock price movements and market volatility. For instance, Seng and Yang [15] developed a dictionary-based sentiment analysis model to examine the link between financial news and stock market volatility. Their algorithm calculates sentiment scores and integrates them into an empirical model for volatility prediction. Results indicate a significant correlation between news sentiment and stock returns, with a 66% prediction accuracy. Despite limitations in data sources and duration, their findings highlight sentiment analysis as a valuable tool for investment decision-making. Similarly, Nyakurukwa and Seetharam [16] examine the relationship between textual sentiment from news and social media and stock returns across four markets (USA, UK, South Africa, and Brazil) from 2016 to 2023. Their findings reveal that social media sentiment strongly influences U.S. stock returns, while news media sentiment has a greater impact in other markets. The study underscores the interplay between these sources, enhancing understanding of financial market dynamics.

Das [17] reviews the integration of sentiment analysis with graph neural networks (GNNs) for stock prediction. The study explains GNN fundamentals, highlights their advantages over traditional methods, and explores various graph structures representing financial data. It discusses sentiment data sources, preprocessing challenges, evaluation metrics, and model performance. By identifying limitations and research gaps, the study provides a roadmap for advancing stock prediction using GNNs and sentiment analysis. Similarly, Dey et al. [18] conducted a comparative analysis of RNN, LSTM, and GRU for stock price prediction across different trends, price ranges, and time intervals. Using three companies' datasets (2000–2020), they found that LSTM and GRU outperformed simple RNN, with GRU yielding the least errors. Shorter time intervals improved model accuracy and reliability. Neeraj et al. [19] reviewed machine learning approaches for big data analysis, covering feature selection, classification, and clustering. They highlighted the limitations of single algorithms and the advantages of hybrid methods. Despite advancements, no universal algorithm exists for all big datasets, emphasizing the need for continuous research and improved computational techniques across various fields.

Despite the success of sentiment analysis in financial applications, there are challenges associated with the accuracy of sentiment classification. Traditional machine learning models, such as Naïve Bayes and Support Vector Machines (SVM), require manual feature extraction and can struggle with complex, non-linear relationships within the data [20]. These models also fail to account for the sequential nature of financial data, where past sentiment can influence future market behavior. This has led to a growing interest in deep learning-based methods that are capable of automatically extracting features and modeling long-range dependencies in textual data.

1.1 Deep Learning for Sentiment Analysis

Deep learning has transformed sentiment analysis by enabling models to learn complex patterns without manual feature engineering. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRUs) have proven effective, especially for processing sequential and unstructured text data [21], [22]. While CNNs excel in text classification by treating text as sequences, they struggle with capturing temporal dependencies [23], which is crucial for financial sentiment analysis. In contrast, RNNs are designed for sequential data processing but suffer from vanishing gradients, limiting their ability to learn long-range dependencies [24], [25].

LSTMs address this issue by using gating mechanisms to regulate information flow, preserving long-term dependencies. However, they are computationally expensive and slow to train. GRUs, introduced by [26], simplify LSTMs by using two gates—update and reset—offering comparable performance with faster training [27]. The update gate determines how much previous state information is carried forward, while the reset gate controls how much past data is forgotten, making GRUs well-suited for financial sentiment analysis.

Several studies highlight GRUs' effectiveness in financial markets. Zhang et al. [28] propose a stock price trend prediction system that forecasts both price movement and growth (or decline) intervals. Using an unsupervised heuristic algorithm, raw transaction data is segmented into clips and classified into four categories (Up, Down, Flat, Unknown). A combination of random forests, imbalance learning, and feature selection improves accuracy, outperforming existing methods on Shenzhen market data. Similarly, Zhou et al. [27] introduce the Minimal Gated Unit (MGU), a simplified recurrent neural network (RNN) gated unit with a single gate. MGU retains the performance of GRUs while reducing complexity, training time, and parameter count. Experiments on sequence data demonstrate its efficiency, making it suitable for RNN applications and easier to evaluate, tune, and study theoretically. Zulqarnain et al. [29] propose a Two-State GRU (TS-GRU) with a feature attention mechanism for sentiment analysis. The model enhances sentiment polarity classification by capturing word relationships and key features. Evaluated on IMDB, MR, and SST2 datasets, TS-GRU achieved accuracies of 90.85%, 80.72%, and 86.51%, respectively, demonstrating its effectiveness in sentiment classification tasks. Adelakun [6] explores deep learning for financial sentiment analysis, comparing GRU and BERT models. The study follows data gathering, preprocessing, downsampling, and classification steps, assessing performance using accuracy, precision, recall, and F1-score. BERT outperformed GRU with 94.28% accuracy, while GRU achieved 93.4%. Both models enhance sentiment analysis, aiding financial forecasting, investment decisions, and market trend identification.

In this study, after reviewing relevant literature, the researchers use the GRU model due to its efficiency, simplicity, and effectiveness in handling sequential data. Unlike LSTM, it has fewer parameters, making it faster and less memory-intensive while maintaining performance. GRU effectively mitigates the vanishing gradient problem, ensuring better long-term dependency learning and faster convergence. Sentiment analysis using GRUs has significant implications for financial decision-making, aiding in stock movement prediction, market sentiment assessment, and trading strategy optimization. Future research will enhance model interpretability and integrate diverse data sources for improved financial analysis.

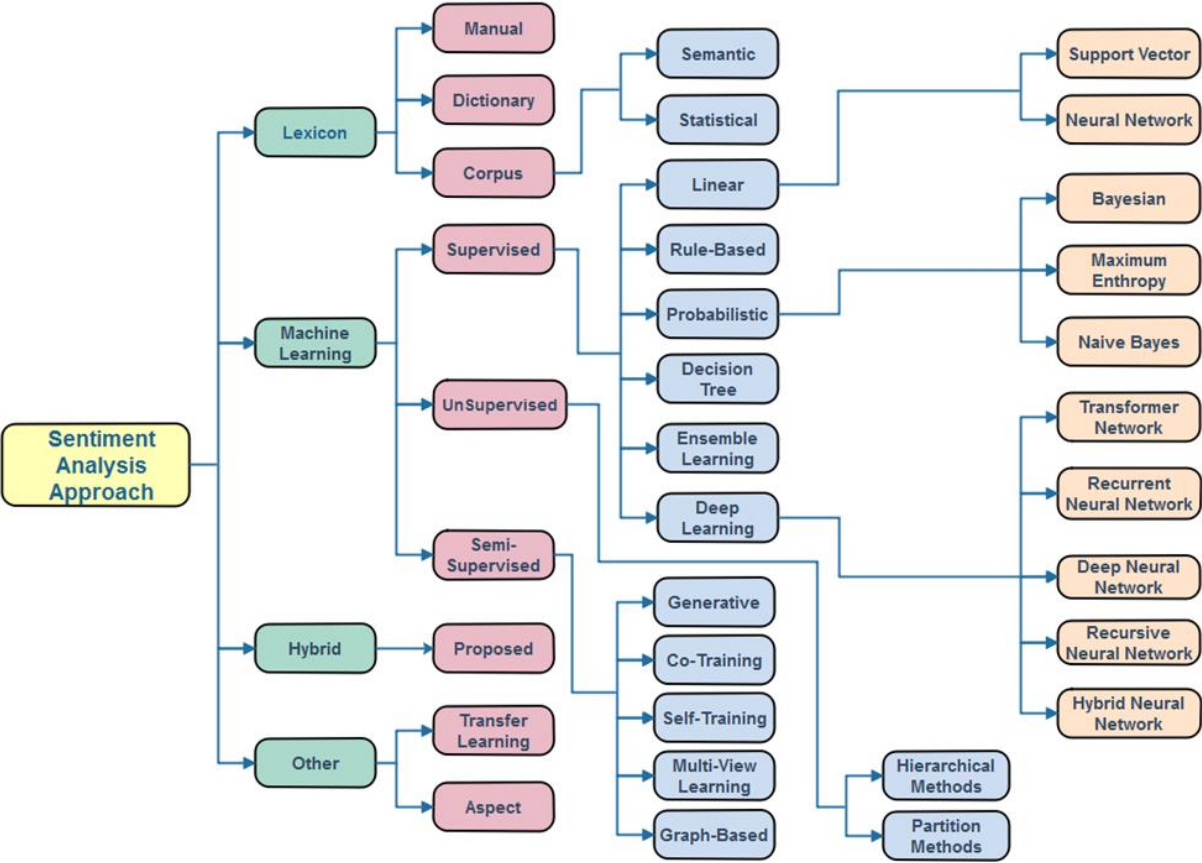


Figure 1. Sentiment Analysis Approach [6], [10]

Figure 1 categorizes sentiment analysis approaches into Lexicon-based, Machine Learning, Hybrid, and other methods. Machine Learning includes Supervised, Unsupervised, and Semi-Supervised techniques, incorporating deep learning models like RNN and Transformer Networks. Hybrid approaches combine multiple methods, while other approaches include Transfer Learning and Aspect-based analysis.

2. Methodology

This study employs a deep learning-based approach using Gated Recurrent Units (GRU) to perform sentiment analysis on financial market text data. The methodology involves data collection, preprocessing, sentiment labeling, feature extraction, model training, evaluation, and application to financial decision-making. Figure 2 shows the step-by-step methodology involved.

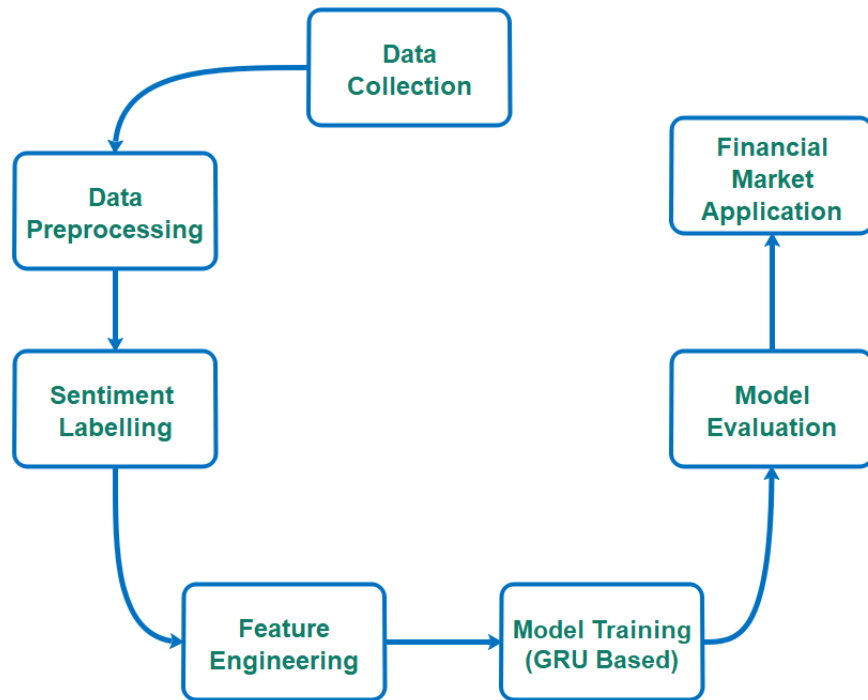


Figure 2. Block Diagram of Sentiment Analysis Process with GRU Model

- i. **Data Collection:** The financial dataset used for sentiment analysis consisted of 5,842 test samples sourced from FiQA and the Financial PhraseBank [30]. The sentiment distribution within the dataset included 3,130 neutral, 1,852 positive, and 860 negative samples. To efficiently process this dataset, essential Python libraries such as Keras, TensorFlow, NumPy, scikit-learn, and PyTorch were used.
- ii. **Data Preprocessing:** Text is cleaned (removing noise, tokenization, lemmatization), and data downsampling is applied to balance sentiment classes.
- iii. **Sentiment Labeling:** Sentiment categories (positive, negative, neutral) are assigned using lexicon-based tools or supervised learning.
- iv. **Feature Engineering:** Text is transformed into word embeddings (Word2Vec, GloVe, BERT), which serve as sequential inputs to the GRU model for capturing contextual dependencies.
- v. **Model Training (GRU-Based):** A Gated Recurrent Unit (GRU) model processes sequential text data, optimized with the Adam optimizer and cross-entropy loss function.
- vi. **Model Evaluation:** Performance is assessed using accuracy, precision, recall, F1-score, confusion matrix, and AUC-ROC curve.
- vii. **Financial Market Application:** The trained model analyzes sentiment trends, correlating results with stock price movements, market trends, and trading volume for decision-making.

3. Result and Discussion

The performance evaluation utilized the GRU model to analyze a financial dataset containing 5,842 reviews, categorized into three sentiment groups: 3,130 neutral, 1,852 positive, and 860 negatives. This approach provided valuable insights into the sentiment distribution and helped assess the model's effectiveness in handling diverse feedback types.

	Sentence	Sentiment
0	The GeoSolutions technology will leverage Bene...	positive
1	<i>ESIonlows, down</i> 1.50 to \$2.50 BK a real po...	negative
2	For the last quarter of 2010 , Componenta 's n...	positive
3	According to the Finnish-Russian Chamber of Co...	neutral
4	The Swedish buyout firm has sold its remaining...	neutral
5	\$SPY wouldn't be surprised to see a green close	positive
6	Shell's \$70 Billion BG Deal Meets Shareholder ...	negative
7	SSH COMMUNICATIONS SECURITY CORP STOCK EXCHANG...	negative
8	Kone 's net sales rose by some 14 % year-on-ye...	positive
9	The Stockmann department store will have a tot...	neutral
10	Circulation revenue has increased by 5 % in Fi...	positive
11	\$SAP Q1 disappoints as #software licenses down...	negative
12	The subdivision made sales revenues last year ...	positive

Figure 3. Data Visualization

Figure 3 presents a data visualization of the first 13 rows of the dataset, offering a snapshot of the structure and content of the data. This showcases the initial entries, highlighting key features and sentiment labels, which are essential for understanding the dataset's distribution and form. It provides a clear overview of the dataset's format, aiding in the subsequent analysis and preprocessing steps.

	Sentence	Sentiment	cleaned_Sentence	sentiment_encoded
0	The GeoSolutions technology will leverage Bene...	positive	geosolutions technology leverage benefon gps s...	2
1	<i>ESIonlows, down</i> 1.50 to \$2.50 BK a real po...	negative	esi lows bk real possibility	0
2	For the last quarter of 2010 , Componenta 's n...	positive	last quarter componenta net sales doubled eurm...	2
3	According to the Finnish-Russian Chamber of Co...	neutral	according finnishrussian chamber commerce majo...	1
4	The Swedish buyout firm has sold its remaining...	neutral	swedish buyout firm sold remaining percent sta...	1
5	\$SPY wouldn't be surprised to see a green close	positive	spy wouldnt surprised see green close	2
6	Shell's \$70 Billion BG Deal Meets Shareholder ...	negative	shells billion bg deal meets shareholder skept...	0
7	SSH COMMUNICATIONS SECURITY CORP STOCK EXCHANG...	negative	ssh communications security corp stock exchange...	0
8	Kone 's net sales rose by some 14 % year-on-ye...	positive	kone net sales rose yearonyear first nine months	2
9	The Stockmann department store will have a tot...	neutral	stockmann department store total floor space s...	1
10	Circulation revenue has increased by 5 % in Fi...	positive	circulation revenue increased finland sweden	2
11	\$SAP Q1 disappoints as #software licenses down...	negative	sap q disappoints software licenses real probl...	0
12	The subdivision made sales revenues last year ...	positive	subdivision made sales revenues last year eur ...	2

Figure 4. Data Visualization of a Cleaned Dataset

Figure 4 displays a data visualization of the first 13 rows from the cleaned dataset, showing the results after preprocessing steps like removing null values, duplicates, and irrelevant data. This refined dataset is now ready for sentiment analysis. The visualization highlights the cleaned structure and ensures that only relevant information, such as sentiment labels and features, remains for further analysis and model training.

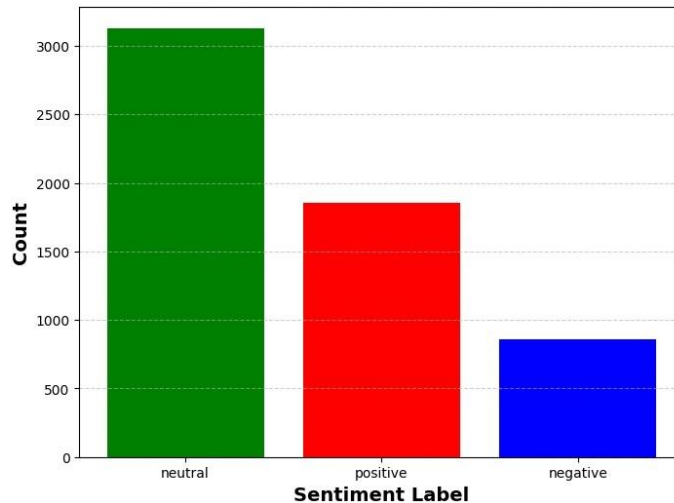


Figure 5. Bar Chart Depicting Sentiment Distribution of Data

Figure 5 presents a bar chart depicting the sentiment distribution within the dataset. It highlights the distribution of three sentiment labels: neutral (3,130 samples), positive (1,852 samples), and negative (860 samples). This visualization provides a clear overview of the class balance, indicating the prevalence of neutral sentiment compared to positive and negative labels, which is crucial for understanding the dataset's characteristics and guiding the model's training process.



Figure 6. Word Cloud for the Sentiment Categories

Figure 6 presents a word cloud for the sentiment categories in the dataset. The cloud visually highlights the most frequently occurring words for each sentiment label (neutral, positive, negative). Words with higher frequency appear larger, offering insight into the key terms associated with each sentiment. This visualization helps identify patterns in language usage, aiding in feature extraction and understanding how different sentiments are expressed within the financial text data.

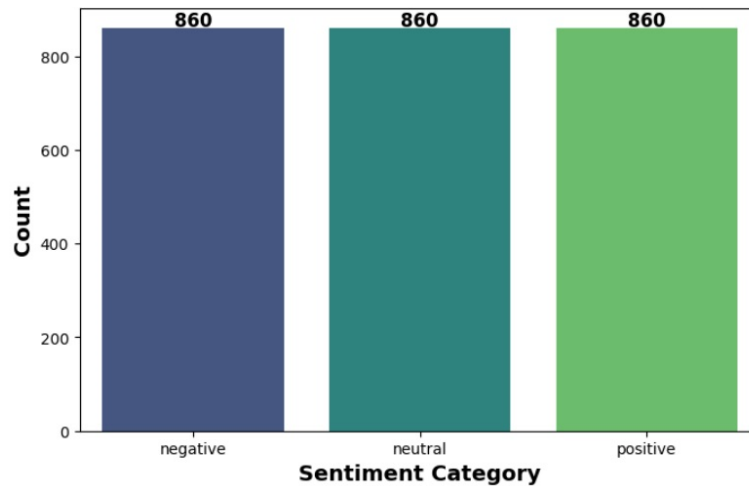


Figure 7. Bar Chart Depicting Distribution of Downsampled Sentiment Categories

Figure 7 illustrates a bar chart depicting the distribution of sentiment categories after downsampling, with each category (neutral, positive, and negative) reduced to 860 samples. This equalization process ensures a balanced dataset, addressing class imbalance issues. The chart shows the adjusted distribution, which is crucial for improving model performance by preventing the model from being biased toward the more dominant sentiment classes during training.

```

147/147 ————— 0s 107ms/step - accuracy: 0.5117 - loss: 1.0175
Epoch 1: val_loss improved from inf to 0.98668, saving model to best_gru_model.keras
147/147 ————— 22s 119ms/step - accuracy: 0.5118 - loss: 1.0174 - val_accuracy: 0.5355 - val_loss: 0.9867 - learning_rate: 0.0010
Epoch 2/20
147/147 ————— 0s 110ms/step - accuracy: 0.5398 - loss: 0.9906
Epoch 2: val_loss improved from 0.98668 to 0.98663, saving model to best_gru_model.keras
147/147 ————— 17s 118ms/step - accuracy: 0.5398 - loss: 0.9906 - val_accuracy: 0.5355 - val_loss: 0.9866 - learning_rate: 0.0010
Epoch 3/20
147/147 ————— 0s 106ms/step - accuracy: 0.5381 - loss: 0.9986
Epoch 3: val_loss improved from 0.98663 to 0.98385, saving model to best_gru_model.keras
147/147 ————— 17s 115ms/step - accuracy: 0.5381 - loss: 0.9985 - val_accuracy: 0.5355 - val_loss: 0.9838 - learning_rate: 0.0010
Epoch 4/20
147/147 ————— 0s 106ms/step - accuracy: 0.5376 - loss: 0.9877
Epoch 4: val_loss improved from 0.98385 to 0.98259, saving model to best_gru_model.keras
147/147 ————— 17s 115ms/step - accuracy: 0.5376 - loss: 0.9877 - val_accuracy: 0.5355 - val_loss: 0.9826 - learning_rate: 0.0010
Epoch 5/20
147/147 ————— 0s 109ms/step - accuracy: 0.5433 - loss: 0.9835
Epoch 5: val_loss improved from 0.98259 to 0.98140, saving model to best_gru_model.keras
147/147 ————— 17s 117ms/step - accuracy: 0.5432 - loss: 0.9835 - val_accuracy: 0.5355 - val_loss: 0.9814 - learning_rate: 0.0010
Epoch 6/20
147/147 ————— 0s 106ms/step - accuracy: 0.5437 - loss: 0.9816
Epoch 6: val_loss did not improve from 0.98140
147/147 ————— 17s 113ms/step - accuracy: 0.5436 - loss: 0.9816 - val_accuracy: 0.5355 - val_loss: 0.9823 - learning_rate: 0.0010
Epoch 7/20
147/147 ————— 0s 108ms/step - accuracy: 0.5410 - loss: 0.9887
Epoch 7: val_loss improved from 0.98140 to 0.98080, saving model to best_gru_model.keras
147/147 ————— 17s 116ms/step - accuracy: 0.5409 - loss: 0.9887 - val_accuracy: 0.5355 - val_loss: 0.9808 - learning_rate: 0.0010
Epoch 8/20
147/147 ————— 0s 105ms/step - accuracy: 0.5365 - loss: 0.9903
Epoch 8: val_loss did not improve from 0.98080
147/147 ————— 17s 112ms/step - accuracy: 0.5365 - loss: 0.9903 - val_accuracy: 0.5355 - val_loss: 0.9814 - learning_rate: 0.0010
Epoch 9/20
147/147 ————— 0s 107ms/step - accuracy: 0.5404 - loss: 0.9843
Epoch 9: ReduceLROnPlateau reducing learning rate to 0.00050000000237487257.
Epoch 9: val_loss did not improve from 0.98080
147/147 ————— 17s 114ms/step - accuracy: 0.5403 - loss: 0.9844 - val_accuracy: 0.5355 - val_loss: 0.9820 - learning_rate: 0.0010
Epoch 10/20
147/147 ————— 0s 104ms/step - accuracy: 0.5342 - loss: 0.9937
Epoch 10: val_loss did not improve from 0.98080
147/147 ————— 16s 111ms/step - accuracy: 0.5342 - loss: 0.9937 - val_accuracy: 0.5355 - val_loss: 0.9821 - learning_rate: 5.0000e-04
Epoch 10: early stopping
Restoring model weights from the end of the best epoch: 7.
37/37 ————— 2s 38ms/step

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Figure 8. Epochs of GRU

Figure 8 displays the training process of the Gated Recurrent Unit (GRU) model across multiple epochs. It shows how the model's performance evolves with each epoch, highlighting changes in metrics such as accuracy or loss. This visualization provides insight into the model's learning progress and convergence behavior, helping to assess whether additional epochs are needed for improved performance or if the model has reached optimal training.

Classification Report:				
	precision	recall	f1-score	support
negative	0.00	0.00	0.00	172
neutral	0.54	1.00	0.70	626
positive	0.00	0.00	0.00	371
accuracy			0.54	1169
macro avg	0.18	0.33	0.23	1169
weighted avg	0.29	0.54	0.37	1169

Figure 9. Classification Report

Figure 9 presents the classification report for the GRU model's performance on the dataset. It includes precision, recall, and f1-score for each sentiment category: negative, neutral, and positive. The report shows that the model has a high recall (1.00) for the neutral category, indicating it correctly identifies neutral sentiment. However, it performs poorly for the negative and positive classes, with both precision and recall values of 0.00. The overall accuracy is 0.54, with macro and weighted averages highlighting the model's limitations and potential for improvement.

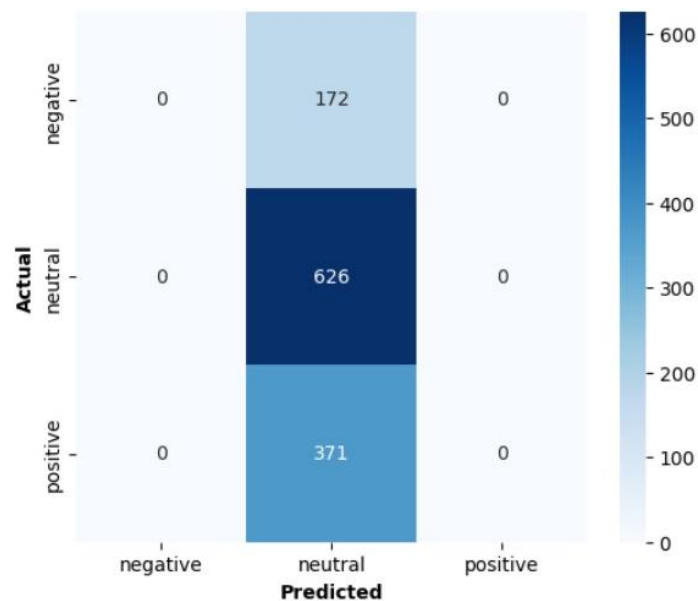


Figure 10. Confusion Matrix

Figure 10 presents the confusion matrix derived from the classification report. The matrix displays the actual sentiment labels versus the predicted ones, highlighting the number of instances correctly classified and where misclassifications occurred. The neutral class shows a high number of correct predictions, whereas the negative and positive classes suffer from significant misclassification. This visualization pinpoints specific weaknesses in the model's ability to differentiate sentiment classes, guiding further model refinement and training strategies for improved accuracy. Overall, the matrix highlights critical improvement areas.

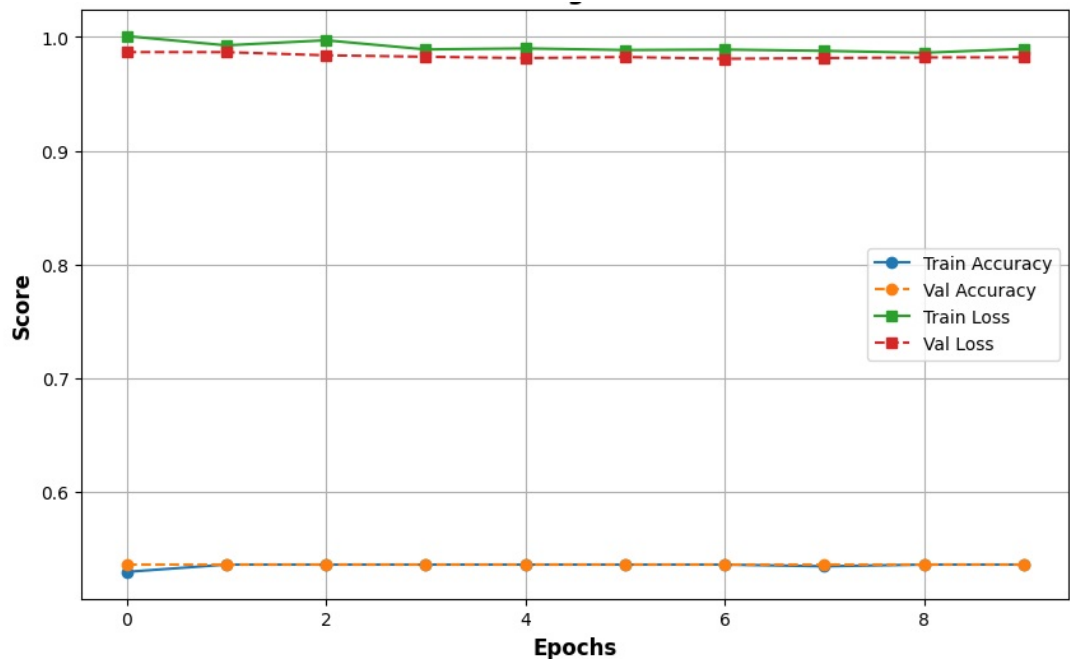


Figure 11. Graphical Illustration of Model Training Performance

Figure 11 displays a line chart illustrating the model's training performance across multiple epochs. It tracks key metrics including accuracy, loss, precision, recall, and F1-score for both training and validation sets. A steady increase in accuracy and F1-score alongside a decrease in loss indicates effective learning and improved predictions. The alignment between training and validation metrics suggests good generalization, while a widening gap may signal overfitting. Data labels on each point provide exact metric values, facilitating trend analysis and pinpointing the best-performing epoch for optimal model performance. Overall, performance improves.

4. Conclusion

This study demonstrates the potential of deep learning-based sentiment analysis in financial markets using a Gated Recurrent Unit (GRU) model. The GRU model successfully captured sequential dependencies in financial text data, offering valuable insights into market trends and investor sentiments. Experimental results indicate that while the model performs well in classifying neutral sentiments, it struggles with accurately identifying negative and positive sentiments, underscoring the need for enhanced data balancing techniques and more refined feature extraction methods. These limitations provide a clear direction for further research. Future studies should expand the dataset to include a broader range of sources such as real-time social media feeds, comprehensive financial news, and macroeconomic indicators to improve model robustness. Additionally, exploring hybrid deep learning architectures, incorporating attention mechanisms, or employing transformer-based models may yield improvements in classification accuracy. Research into explainable AI techniques would also be beneficial, offering deeper insights into the model's decision-making processes and enhancing transparency in financial predictions. Overall, this study contributes significant insights into the application of GRU-based deep learning for financial sentiment analysis and lays a solid foundation for future work. Advancing this research will help bridge the gap between theoretical developments and practical financial applications, ultimately supporting better investment strategies and market forecasting, and inspiring further innovation in the field. These findings encourage continued exploration and development.

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