HYBRID DEEP LEARNING FOR FOREX PREDICTION: INTEGRATING SOCIAL MEDIA SENTIMENT AND TECHNICAL INDICATORS

Sampath M.K.T.

239175P

MSc in Data Science & Artificial Intelligence

Department of Computer Science
Faculty of Engineering

University of Moratuwa
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DECLARATION

I declare that this is my own work and this thesis/dissertation does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other University or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text. I retain the right to use this content in whole or part in future works (such as articles or books).

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The above candidate has carried out research for the Master thesis under my supervision. I confirm that the declaration made above by the student is true and correct.

Name of the Supervisor: Thanuja D. Ambegoda

Signature of the Supervisor: Date: 25th June 2025

ABSTRACT

This study proposed a new way to predict currency prices in the Forex market by combining statistical indicators with social media sentiment analysis. The research classifies tweets from influential financial analysts as positive, negative, or neutral and combines sentiment analysis results with technical indicators derived from historical price behavior. This mix of methods improves pattern recognition in the market and leads to smarter trade choices that are more likely to be right.

The VADER Sentiment library, a powerful sentiment analysis tool, has been employed to analyze Forex-related tweets of the most influential market players. The study identifies the most influential tweets based on impact engagement measures (likes, replies, and retweets) and selects the most relevant technical indicators. A dataset comprising ten technical indicators, along with news tweets from influential players in USD and EURO trades, has been collected for the study.

A prediction model was built using several deep learning approaches including Gated Recurrent Units (GRU), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, Recurrent Neural Networks (RNN), and some combined models. The LSTM-CNN-Attention model, which is a recent and specialized architecture for Forex data, was also considered in our experiment. In addition, the best-performing models were tested both with and without impact ratio - Sentiment Score of Social media Text.

To see which worked best, their performance is compared using key points like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and the R-squared score. Comparative analysis reflected the weaknesses and strengths of individual models, revealing the effectiveness of the ensemble strategy.

The research also points out its limitations. It includes a detailed look at what other popular models are being used in predicting the Forex market. The results show that combining sentiment analysis with technical indicators improves how accurately it can be predicted Forex prices in this research. The hybrid GRU-LSTM model was the best among the deep learning options in this research experiment. It outperformed all of the earlier methods used by other researchers on the EUR/USD Forex data.

Keywords: Forex price prediction, Forex price forecasting, sentiment analysis, LSTM, GRU, CNN, RNN, Twitter Sentiment, Technical Indicators

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

Abbreviation	Description
Forex	Foreign Exchange Market
AI	Artificial Intelligence
LSTM	Long Short-Term Memory
GRU	Gated Recurrent Unit
RNN	Recurrent Neural Network
CNN	Convolutional Neural Network
USD	United States Dollar
EUR	Euro
API	Application Programming Interface
RNN	Recurrent Neural Network
ANN	Artificial Neural Network
SVR	Support Vector Regression
MAE	Mean Absolute Error
MSE	Mean Squared Error
RMSE	Root Mean Squared Error
BPTT	Backpropagation Through Time
VADER	Valence Aware Dictionary and sentiment Reasoner
PCA	Principal Component Analysis
t-SNE	t-distributed Stochastic Neighbor Embedding

CHAPTER 1

INTRODUCTION

The Foreign Exchange Market is one of the largest financial markets in the world, with a daily trading volume of 7.5 trillion US dollars. It operates on high risks and highly potential chances of profit for the traders. Traders make a profit by predicting which way the exchange rate between two currencies will move. But mistakenly judged predictions about trends in Forex usually create higher losses compared to other financial markets.

Artificial Intelligence (AI) can sift through large chunks of data and pick up on patterns or trends that would be difficult or even impossible for human to notice on their own. Social media sites like Twitter produce a vast amount of daily text about EUR/USD Forex Trading. AI-based sentiment analysis programs are deployed to extract information from social media data and identify emerging trends and shifts in opinion.

On the other hand, traditional technical indicators like moving averages, Bollinger Bands, and stochastic oscillators are analyzed by Forex traders to identify common patterns and trends to make quick trading decisions. These indicators can be used to identify a variety of market conditions, including trends, momentum, overbought /oversold levels, and support resistance levels too.

A new approach in forecasting Forex price movement using AI-driven social media sentiment analysis and technical indicators is introduced in this research, including a new ratio named Impact Engagement Ratio. The new model is stronger and more accurate compared to either of these variables taken alone in predicting the price movement in the United States Dollar (USD) and Euro (EUR). It is assumed that the sentiment analysis of social media can be transferred to identify upcoming trends and shifts in public opinion of influential stakeholders who may not yet be present in the price data. The technical indicators can be used to provide a numerical and objective assessment of the market.

A predictive model is developed to provide Forex traders with an accessible tool to make intelligent trading choices in this research. Long short term memory (LSTM) networks [11], Gated recurrent units (GRUs) are selected as Key AI algorithms after many experiments, and Sentiment Analysis Algorithms (VADER) were selected depending on the results of similar works performed by other researchers, and it is further tuned according to the experimental results. RNN and CNN have also been considered to improve the accuracy of prediction while implementing the proposed solution.

CHAPTER 2

RESEARCH PROBLEM

Figuring out which way forex prices will go is challenging because the market is complex and moving fast. Many global factors, such as politics, economic updates, supply and demand, and trader emotions, can affect currency prices. There's a real chance to make big profits, but if the predictions are wrong, you could end up losing a lot.

Most traditional forecasting methods tend to be pretty limited because they usually only look at one kind of data. These methods either look at news articles to understand public mood or study past price patterns using technical tools. However, using only one of these approaches does not fully explain how the Forex market behaves, since it often moves in unpredictable and fast-changing ways. The connection between market feelings, economic data, and price changes is not simple or stable, which makes it hard for these methods to work well on their own.

A major difficulty in predicting Forex prices comes from the ever-changing nature of market conditions. The Forex market doesn't follow a single pattern—it shifts between different states such as trending, ranging, consolidating, and volatile phases. Each of these market types behaves differently and can affect how useful certain indicators or strategies are. For example, a strategy that works well during a strong uptrend might give poor results when prices are moving sideways. Sudden changes triggered by global news or unexpected economic events can quickly transform the market's behavior, making it harder for prediction models to stay accurate.

This unpredictable nature adds another layer of complexity to forecasting. Often, it's not clear what type of market is present until it has already changed. A prediction model that performs well in calm markets might fail when conditions become erratic. This means that effective forecasting tools need to be flexible and responsive to market shifts. By bringing together real-time social media sentiment and proven technical indicators, this study aims to create a model that can adjust to various market environments and improve prediction accuracy, helping traders make more informed decisions under different trading conditions.

This study is all about finding better ways to predict Forex prices by combining different methods. It brings together two different sources of information: (1) tweets from key figures in the Forex world to understand current market sentiment, and (2) some of the best-performing technical indicators that show patterns based on past price data. The idea is that while technical indicators help spot trends from history, social media gives clues about what people think now and where the market might go next. Platforms like Twitter are now a key place for traders to form opinions and make decisions.

By merging these two types of data, this research aims to build a stronger and more accurate prediction model. The goal is not only to explore this in theory but also to create a useful tool for real Forex traders. This model should help them make smarter and safer trading choices, lower their risks, and possibly increase their profits.

CHAPTER 3

RESEARCH OBJECTIVES

The following research objectives and the novelty of the novel methodology are outlined as the objective of this experiment:

1. **Comprehensive Dataset:** Collecting a full dataset of historical technical indicator data and tweet news of the most influential individuals on USD and EURO trade in the Forex market. This study gives researchers a lot of useful details that they can use for their upcoming work.

2. **Algorithms for Sentiment Analysis:** Designing and developing a sentiment analysis algorithm that is capable of classifying tweets into positive, negative, or neutral sentiment categories. This should be able to create sentiment analysis customized to the financial domain.

3. **Explore Relationship**: Look into how social media feelings, technical signals, and Forex market movements are connected.

4. **Impact Engagement Ratio of Tweets**: Introducing a new impact ratio based on the average tweet shared in the previous days to enhance the forecasting model's accuracy and strength. This novel approach gives a valuable dimension to understanding the influence of social media sentiment on market behavior and trends in the Forex market.

5. **Intelligent Predictive Model**: Developing a predictive model to evaluate the accuracy and effectiveness of the combined approach in Forex market price predictions. Using social media feelings and technical signs together is a pretty good way to predict where the market might go.

The above research objectives are identified in order to explore the influence of social media sentiment and technical indicators on Forex market trends. The research has a huge potential to provide valuable insights into the field of financial analysis with regard to each research objective.

CHAPTER 4

RESEARCH CONTRIBUTION

This study adds some important insights into how to predict Forex prices and understand the market conditions. This research emphasizes its main contributions as follows:

1. **Integrated Approach:** Combining technical indicators with social media sentiment gives a better way to predict Forex prices. Based on sentiment analysis of opinion leaders' tweets and historical prices, the research provides an in-depth picture of market movements leading to smarter trading decisions.

2. **Enhanced Predictive Accuracy:** The new approach and the models are designed to make Forex price predictions much more accurate. The research focuses on using smarter sentiment analysis methods and picking out the most useful features from technical indicators and sentiment results. The goal is to improve how accurately it predicts price changes.

3. **Identification of Influential Financial Experts:** The study focuses on identifying top influencers in the Forex market based on audience impact engagement metrics such as retweets, likes, and replies. This identification process contributes to a better understanding of the influence of key individuals on market sentiment and price movements.

4. **Comprehensive Dataset Collection:** The research involves the collection of a comprehensive dataset of historical trading data (technical indicators) and tweet news from influential financial experts. This dataset contributes to the availability of valuable resources for further research and analysis in the field of Forex market prediction.

The contributions demonstrate the novelty and significance of this research in advancing the understanding and predictive capabilities of Forex price movements through the integration of social media sentiment analysis and technical indicators.

CHAPTER 5

EXPERIMENTAL FRAMEWORK

1. **Data Gathering - Forex Data:**

   Collected historical Forex market data for the EUR/USD currency pair from www.histdata.com. The dataset also includes minute-level Forex market data, made up of 213,096 rows and 19 features. While a few data points are missing in some columns, like stoch_k (47 missing values) and ichimoku_a (26 missing values), they were properly handled during data cleaning. The average price level stays close to 1.083, showing low fluctuation, as also reflected in the ATR average of 0.000117. Momentum and trend indicators show wider changes, especially in stoch_k, which ranges from 0 to 100. The ADX, which measures trend strength, averages around 24.67, suggesting that the market had moderate trends over the studied period.

2. **Data Gathering - Tweet Data:**

   Sentiment data was extracted from (https://rapidapi.com/MDCYT/api/twitter291) by running a Python script daily over the past 9 months. Tweets from leading currency traders, financial analysts, and economists have been used to build, train, and test these models. It includes 3,883 tweets posted between November 1, 2023, and August 23, 2024, with the highest number of tweets shared on August 1, 2024. Each tweet contains information such as the date and time it was posted, how many likes it received, a sentiment score between 0 and 1, and a label indicating whether the sentiment is Positive, Neutral, or Negative. Most tweets were Neutral (2,563), followed by Positive (863), and then Negative (457). Interestingly, neutral tweets also received the highest average number of likes (360), suggesting that people may have engaged more with balanced or informative content.

3. **Data Preprocessing:**

   Cleaned and preprocessed the collected data, including handling missing values, normalizing time series data, and preparing text data for sentiment analysis.

4. **Feature Engineering:**

   The feature engineering process began with 41 technical indicators (Statistical Indicators), Sentiment Scores, and Raw Market Data which were systematically evaluated to remove redundancy and retain the most informative features. And also, to deal with multicollinearity, a correlation analysis is performed with Autoencoders to see how the variables relate and affect the model's performance. Highly correlated pairs, like SMA_20 and Bollinger Middle (correlation = 1), and RSI_14 and CMO_14 (correlation = 1), were identified, and only one feature from each pair was retained.

All derived features were computed using previous or immediate closing prices rather than the current close, ensuring temporal consistency and preventing data leakage.

This process gave a powerful, compact and effective set of 17 features that emphasize the main patterns in how the Forex market moves. The final feature set ensured a balanced representation of market trends, momentum, and volatility, enhancing the model's ability to learn from meaningful patterns.

5. **Technical Indicators:**

The technical indicators listed below were chosen based on correlation coefficients - how closely they relate to each other. Technical indicators play a crucial role in understanding market behavior and making informed trading decisions.

1. Trend indicators help determine the direction and strength of market movements. Among these, the *Ichimoku Conversion Line (Tenkan-sen)* and *Ichimoku Base Line (Kijun-sen)* are commonly used; the former calculates the midpoint of the highest high and lowest low over the past 9 periods to capture short-term trends, while the latter does the same over a 26-period window to provide broader trend confirmation and support/resistance levels. *Senkou Span A* and *Senkou Span B*, components of the Ichimoku Cloud, are plotted 26 periods ahead to visualize future support and resistance zones—Span A averages the Conversion and Base Lines, while Span B is the midpoint of the 52-period high and low, offering a more stable reference. The *Parabolic SAR* is another trend-following indicator that visually marks potential reversals and dynamic support/resistance levels using dots placed above or below the price chart. The *Average Directional Index (ADX)*, part of the Directional Movement Index (DMI) system, measures trend strength without indicating direction, with values above 25 typically signifying a strong trend.

2. Momentum indicators assess the rate at which prices are changing, helping to detect the strength behind price movements. The *Moving Average Convergence Divergence (MACD)*, calculated as the difference between the 12- and 26-period exponential moving averages (EMAs), highlights trend direction and momentum. A 9-period EMA of the MACD line, known as the *MACD Signal*, is often used to generate buy or sell signals based on crossovers. The *Rate of Change (ROC)* measures the percentage difference between the current price and its value a specific number of periods ago, signaling potential overbought or oversold conditions. *On-Balance Volume (OBV)* accumulates volume data based on price movement direction to confirm trends—rising OBV suggests accumulation, while falling OBV indicates distribution. The *Accumulation/Distribution Index (ADI)* blends price and volume to detect divergences, highlighting possible shifts in market sentiment.

3. Volatility indicators quantify the extent of price fluctuations over time. The *Average True Range (ATR)* gauges market volatility by averaging the true range over a defined period, with higher ATR values signaling greater price variability. *Bollinger Bands* provide a visual range for price movement based on standard deviations from a moving average; the *Upper Band* suggests overbought levels, while the *Lower Band* signals oversold conditions.

4. Price features such as *Open*, *High*, and *Low* represent fundamental market data. The *Open* reflects the initial trading price for a given period and is often used to identify intraday gaps or market sentiment. The *High* marks the peak price within a timeframe, useful for breakout strategies, while the *Low* identifies the lowest point, serving as a key level for support analysis and trend strength evaluation. Together, these indicators and features provide a comprehensive framework for technical analysis, guiding traders through complex market dynamics.

The following technical indicators were selected after carefully analyzing the impact on the final results.

Table 5.1

Technical Trend Indicators Utilized in Forecasting Models

No	Type	Indicator/Feature	Description
1	Trend Indicators	Ichimoku Conversion Line (Tenkan-sen)	Midpoint of highest high and lowest low over 9 periods
2		Ichimoku Base Line (Kijun-sen)	Midpoint of highest high and lowest low over 26 periods
3		Ichimoku A (Senkou Span A)	Midpoint between Conversion and Base Line, plotted 26 ahead
4		Ichimoku B (Senkou Span B)	Midpoint of 52-period high and low, plotted 26 ahead
5		Parabolic SAR (psar)	Time/price-based trend-following dots above/below price
6		ADX (Average Directional Index)	Measures strength of a trend (not direction)
7	Momentum Indicators	MACD	Difference between 12- and 26-period EMAs
8		MACD Signal	9-period EMA of MACD line
9		ROC (Rate of Change)	% change from price n periods ago
10		OBV (On-Balance Volume)	Cumulative volume depending on price direction
11		ADI (Accumulation/Distribution Index)	Compares price and volume to detect divergence
12	Volatility	ATR (Average True Range)	Measures average market volatility over a set period
13		BB Upper	Upper Bollinger Band = SMA + (std deviation × factor)
14		BB Lower	Lower Bollinger Band = SMA - (std deviation × factor)
15	Price Featur	Open	Price at the beginning of the period
16		High	Highest price during the period
17		Low	Lowest price during the period

6. **Sentiment Analysis:**

The selection of an optimal sentiment analysis tool was critical to accurately capture market sentiment from influencer tweets without being misled by financial jargon. While domain-specific models like FinBERT are popular for analyzing structured financial texts (e.g., earnings reports or news articles), they underperform on informal, emotion-driven social media content. Our experiments compared VADER and FinBERT on a corpus of Forex-related tweets, focusing on influencers' non-technical language (e.g., "The EURO is collapsing—time to short!" or "USD strength is unstoppable! 💪"). VADER demonstrated superior adaptability to this context, efficiently parsing slang, emojis, and hyperbolic language, whereas FinBERT often misclassified sentiments due to its reliance on formal financial terminology.

This aligns with our objective of measuring raw emotional impact rather than technical analysis. VADER's rule-based approach also offered computational advantages, enabling real-time processing of large tweet volumes without GPU dependency.

7. **Impact Ratio:**

   The Impact Ratio is a metric especially designed to quantify the influence of tweets on the EUR/USD exchange rate. It combines **sentiment analysis** with **engagement metrics** to measure how public discourse and market sentiment affect currency movements.

   Impact Ratio = Avg(Likes | Shares | Comments) × Sentiment Score

Where:

- **Likes**: Represents the engagement or popularity of the text (e.g., the number of likes, retweets, or shares).
- **Sentiment Score**: Represents the emotional tone of the text, derived from sentiment analysis from VADER. A positive score indicates bullish sentiment (favoring the Euro), while a negative score indicates bearish sentiment (favoring the US Dollar).

When looking at the EUR/USD pair, the Impact Ratio is further customized to include certain keywords as follows:

- **EURO-Related Keywords**: If the text contains keywords like “EURO,” “European Union,” or “EU,” the Impact Ratio is **doubled** (if the sentiment is positive).
- **USD-Related Keywords**: If the text contains keywords like “USD,” “United States,” or “USA,” the Impact Ratio is **doubled and made negative** (if the sentiment is negative).
- **Neutral Cases**: If neither EURO nor USD keywords are present, the Impact Ratio is calculated as the product of likes and sentiment score without adjustments.

Here's a simple table showing some example calculations of the Impact Ratio for different scenarios:

Table 5.2

Impact Ratio Calculation

Text	Likes + Shares	Sentiment Score	Keywords	Impact Ratio Calculation	Final Impact Ratio
The EURO is strong today! #EURO	100	0.8 (positive)	EURO	$100 \times 0.8 \times 2$	160
The USD is weak. #USD	50	-0.6 (negative)	USD	$50 \times (-0.6) \times 2$	-60
The market is stable	20	0.1 (neutral)	None	$20 \times 0.1 \times 1$	2
EURO faces challenges	80	,-0.4 (negative)	EURO	$80 \times (-0.4) \times 2$	-64
USD gains strength	120	0.7 (positive)	USD	$120 \times 0.7 \times 2$	-168

- A high **Positive Impact Ratio** indicates strong positive sentiment about the Euro or strong negative sentiment about the US Dollar, suggesting a potential rise in the EUR/USD exchange rate.
- A high **Negative Impact Ratio** indicates strong negative sentiment about the Euro or strong positive sentiment about the US Dollar, suggesting a potential decline in the EUR/USD exchange rate.
- **Zero Impact Ratio** indicates either low engagement or neutral sentiment, suggesting minimal impact on the EUR/USD exchange rate.

The Impact Ratio is a powerful tool for analyzing the influence of sentiment and engagement on currency movements, providing traders and researchers with actionable insights into the EUR/USD market.

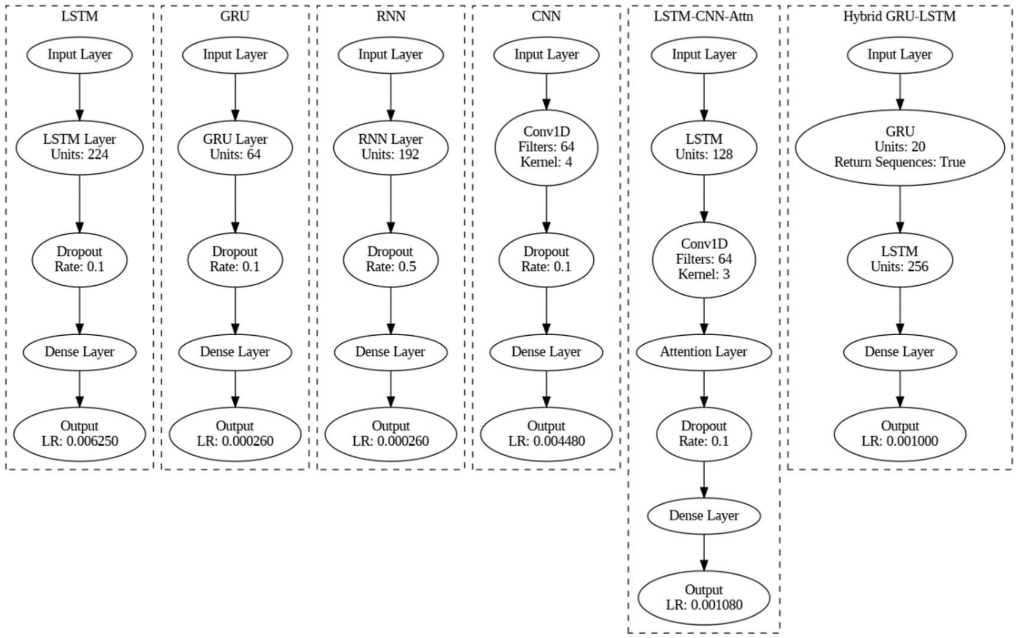
8. **Model Selection and Architecture Design:**

LSTM, GRU, RNN, CNN, LSTM-CNN-Attention, VADER, and hybrid architectures combining two models were considered for time series forecasting and sentiment analysis tasks. We also tested LSTM-CNN-Attention model, which is a newer and more advanced design created specifically for Forex data. The results of both with and without the impact ratio were compared with regard to best best-performing model.

Based on previous research and our initial tests, GRU and LSTM models consistently performed better than standard RNNs, likely because they handle long-term dependencies more effectively. As a result, we also decided to include a hybrid LSTM-GRU model in our experiments. [2]

Figure 5.1

Proposed Model Architectures



9. **Model Training and Validation:**

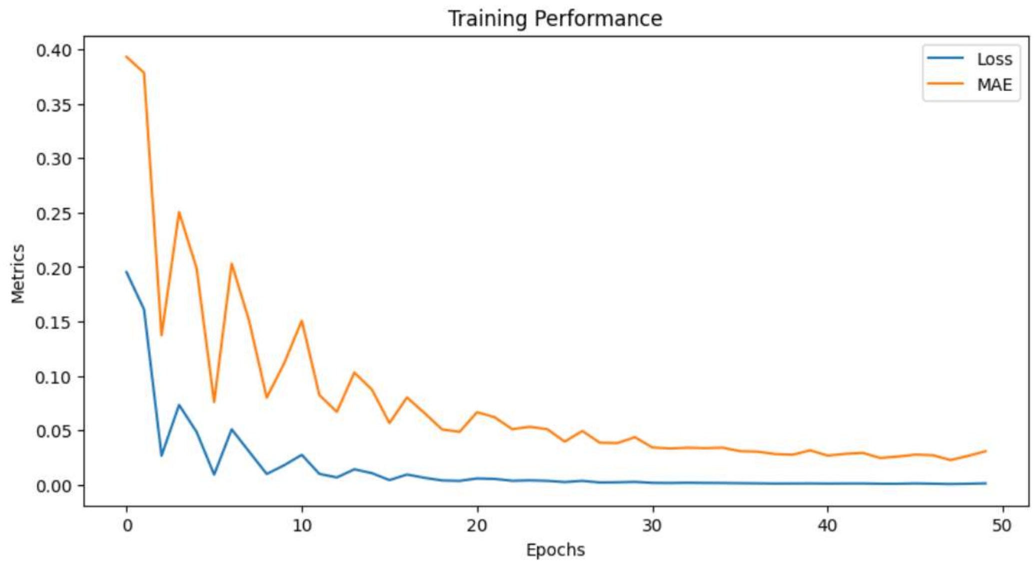
   Training was carried out using backpropagation through time (BPTT) and optimized with gradient-based techniques like Adam optimizer. Given the computational demands of the dataset and the constraints of running on Google Colab, model training was optimized using **model check pointing** to save progress and avoid retraining from scratch. This was especially helpful due to the high data load and the extended time required for training deep learning models. The dataset was split such that **20%** of the data was reserved for testing, ensuring the model's ability to generalize to unseen data.

10. **Hyperparameter Tuning:**

    Special attention was given to designing the network architecture, carefully selecting the number of layers, hidden unit sizes, and input-output dimensions (learning rate, batch size, and network architecture) to match the temporal nature of the Forex and sentiment data. The Hyperparameter Tuning was done using Kera's Tuner to optimize the models' performance.

Figure 5.2

Model Training Performance



To optimize the deep learning models for Forex price prediction, Keras Tuner's Random Search was used to fine-tune key hyperparameters, focusing on minimizing validation loss.

Table 5.3

Hyperparameters of Deep Learning Models for Forex Prediction

No	Parameter	Models	Range / Options
1	units	LSTM, GRU, RNN	32 to 256 (step=32)
2	cnn_filters	CNN, LSTM-CNN-Attn	32 to 128 (step=32)
3	cnn_kernel	CNN, LSTM-CNN-Attn	2 to 5
4	lstm_units	LSTM-GRU, LSTM-CNN-Attn	32 to 256 (step=32)
5	gru_units	LSTM-GRU	32 to 256 (step=32)
6	dense_units	LSTM-GRU	32 to 256 (step=32)
7	dropout	All models	0.1 to 0.5 (step=0.1)
8	lstm_dropout	LSTM-GRU	0.1 to 0.5 (step=0.1)
9	gru_dropout	LSTM-GRU	0.1 to 0.5 (step=0.1)
10	learning_rate	All models	1e-4 to 1e-2 (log sampling)

In this study, we implemented a comprehensive hyperparameter tuning framework to systematically explore and optimize multiple deep learning architectures for Forex price prediction. The experiment setup was designed to accommodate various recurrent neural network (RNN) variants—namely LSTM, GRU, and SimpleRNN—along with convolutional neural networks (CNN) and hybrid models that combine convolutional, recurrent, and attention mechanisms. By making use of the Keras Tuner library, our approach enabled automated and flexible tuning of critical architectural and training parameters across diverse model types, allowing for a fair and consistent comparison.

The hyperparameter search function accepts the model type and input shape as inputs and constructs the corresponding neural network with adjustable components. For simpler models such as LSTM, GRU, and RNN, a sequential architecture was employed, allowing for straightforward specification of the number of recurrent units, dropout rate, and learning rate. In the case of CNN models, the number of convolutional filters, kernel sizes, and pooling layers were also made adjustable. More complex hybrid models, including the LSTM-CNN-Attention and the LSTM-GRU combination, were built using the Keras Functional API. These models incorporate parallel branches and attention layers, with tunable parameters such as the number of LSTM and GRU units, dense layer sizes, and dropout rates. This design choice enabled flexible manipulation of the internal model architecture during the tuning process.

Key hyperparameters across all models included the number of units or filters (ranging from 32 to 256 depending on the layer type), dropout rates between 0.1 and 0.5 for regularization, kernel sizes for convolutional layers, and the learning rate for the Adam optimizer, sampled logarithmically between 1e-4 and 1e-2. The models were compiled with Mean Squared Error (MSE) as the loss function, reflecting the regression nature of the forecasting task. By adjusting these hyperparameters within a defined search space, the setup aimed to balance model complexity and generalization, which in turn helped improve prediction accuracy. Early stopping and validation splits were applied to prevent overfitting and ensure reliable performance evaluation during the hyperparameter optimization.

This adaptable and modular hyperparameter tuning setup allowed for an extensive examination of different model configurations, enabling data-driven selection of the most effective architecture and training strategy. The approach supported the discovery of optimal models suited to the characteristics of the Forex time series data, laying a solid foundation for further analysis and deployment in practical forecasting applications.

Table 5.4

Optimized Hyperparameters of Deep Learning Models for Forex Prediction

No	Model	Best Hyperparameters
1	LSTM	Units: 224, Dropout: 0.1, Learning Rate: 0.00625
2	GRU	Units: 64, Dropout: 0.1, Learning Rate: 0.00026
3	RNN	Units: 192, Dropout: 0.5, Learning Rate: 0.00026
4	CNN	Filters: 64, Kernel Size: 4, Dropout: 0.1, Learning Rate: 0.00448
5	LSTM-CNN-Attn	CNN Filters: 64, Kernel: 3, LSTM Units: 128, Dropout: 0.1, Learning Rate: 0.00108
6	Hybrid LSTM-GRU	LSTM Units: 256, GRU Units: 224, Dense Units: 128, Dropouts: 0.2/0.2, LR: 0.00075

11. **Testing and Evaluation:**

Test the trained models on unseen data to evaluate their predictive power and generalization to new input sequences. The performance of the model is evaluated using various metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared score.

$$MSE = \frac{\sum_{i=1}^{n}(True - Prediction)^2}{n}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(True - Prediction)^2}{n}}$$

$$MAE = \frac{\sum_{i=1}^{n}|True - Prediction|}{n}$$

$$R^2 = 1 - \frac{\overset{\text{Sum Squared Regression Error}}{SS_{Regression}}}{\underset{\text{Sum Squared Total Error}}{SS_{Total}}}$$

The integration of reinforcement learning and meta-learning in Forex forecasting presents a promising avenue for future research based on the current proposed models. These advanced learning paradigms aim to develop adaptive models capable of continuously improving performance by learning from interactions with dynamic market environments. Reinforcement learning, in particular, enables agents to optimize trading strategies through trial-and-error by receiving feedback from the market, thereby aligning closely with the decision-making processes in real-world trading. Meta-learning, or "learning to learn," further enhances model adaptability by enabling systems to generalize across various market regimes and rapidly adjust to new conditions with minimal additional training. Together, these approaches offer the potential to create robust, self-improving predictive frameworks that respond intelligently to evolving patterns in financial time series data. Future work should explore the integration of these techniques with existing models and evaluate their effectiveness in live trading scenarios under varying economic conditions.

Forecasting models are shifting towards more interpretable and data-efficient paradigms. Explainable AI (XAI) techniques such as SHAP and LIME are recommended to unpack model decisions, enabling more transparent trading systems.

In addition, computer vision techniques can be introduced to enhance Forex forecasting by automatically identifying complex chart patterns such as hammer candlesticks and other significant formations. By leveraging image recognition and deep learning models, computer vision can analyze visual market data more effectively than traditional rule-based methods, enabling faster and more accurate pattern detection. This integration could improve the precision of trading signals and provide deeper insights into market behavior.

CHAPTER 6

LIMITATIONS

This research identified some limitations and challenges as listed below when it comes to using sentiment analysis and technical indicators to predict financial trends.

6.1 Data Quality and Noise Challenges

The presence of spam and other unwanted content on social media can really affect the overall quality of the content. Fake accounts, bots, and irrelevant content can be found on social media platforms, which can skew the data and add noise. This may have an effect on the precision and dependability of sentiment analysis findings and ensuing market forecasts.

6.2 Selection of Sentiment Analysis Algorithms and Technical Indicators

The study's findings may be greatly impacted by the selection of sentiment analysis algorithms and technical indicators. The effectiveness of various algorithms and indicators can vary depending on the features and context of the Forex financial market.

6.3 Generalizability to Other Financial Markets

This study's findings won't apply to other financial markets due to the wide variations in sentiment patterns, behavior, and market changes.

6.4 Data Bias

The data taken from the social media platform could be wrong because it only represents the market segment where the platform is popular. The information gathered may be only partially true. This error in the data can dramatically impact on the results of the sentiment analysis, besides market forecasts that end up being incorrect.

6.5 Other External Factors

The appearance of new events or the information that could not be caught by the Tweets which are related to the market sentiment could lead the market to behave differently.

6.6 Market Volatility

Financial markets can change really quickly and unexpectedly because of different things happening around the world. Financial markets are pretty unpredictable, and trying to guess where they'll go just by looking at feelings or charts isn’t always reliable, especially during periods of sharp volatility.

6.7 Regulatory Changes

Changes in regulations happen all the time, and it’s important to keep up with them, especially when the market is constantly shifting.

6.8 Ethical Considerations

Using social media data to predict financial trends brings up some ethical questions, like whether it's right to use people's private data, who really owns the data, and how it might be misused.

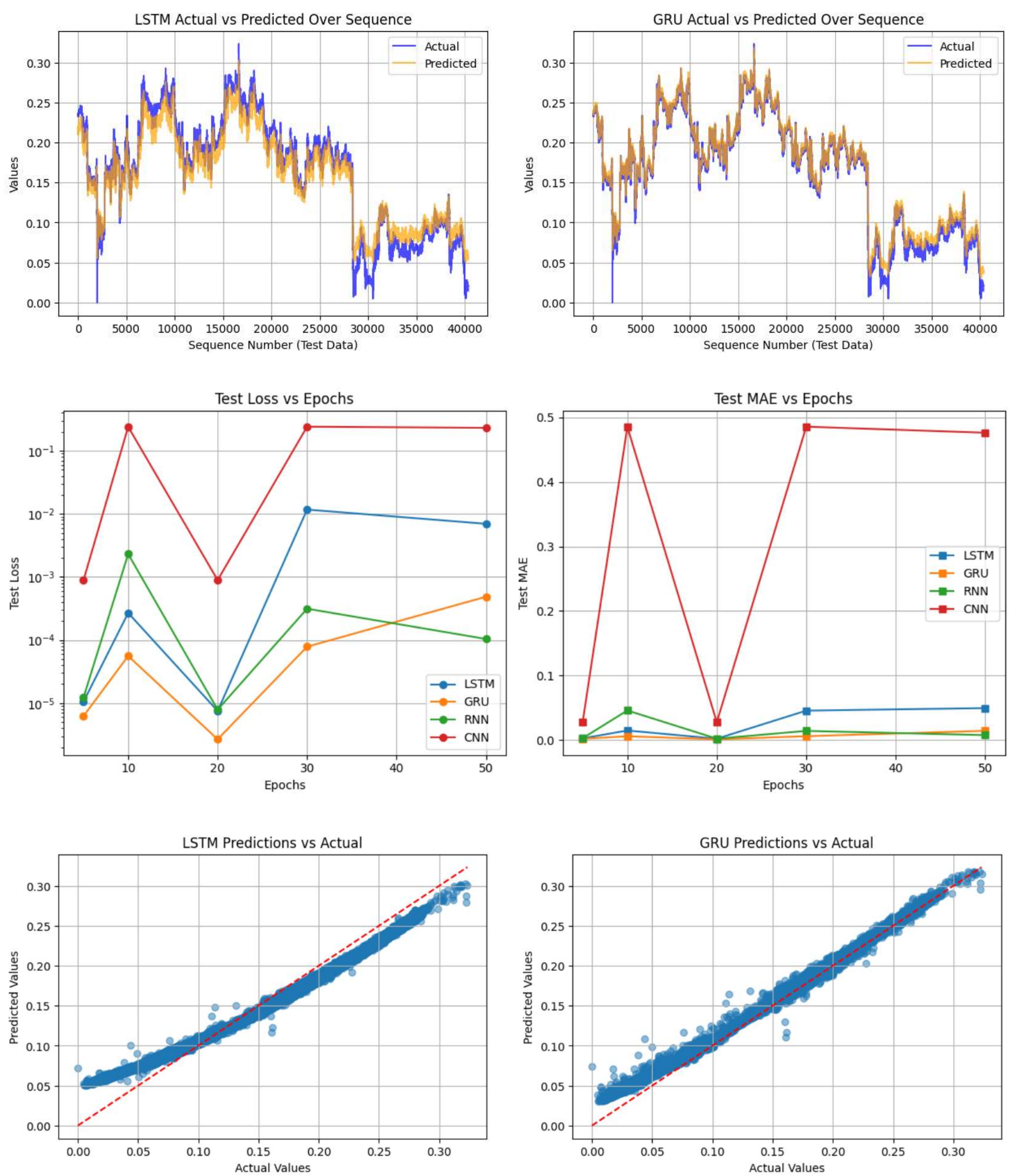
CHAPTER 7

CONCLUSIONS AND RECOMMENDATIONS

This study contrasted the performance of LSTM, GRU, RNN, LSTM-CNN-Attention, and CNN models for time series forecasting with different epoch configurations. The results show that GRU consistently performed better in most cases, particularly at smaller epochs, with the lowest test loss and MAE across different iterations.

Figure 7.1

Model Testing Performance



For lower training epochs (5, 10, 20, and 30), GRU outperformed other models, with lowest MAE and MSE and highest R^2 score, notably at epoch 30 ($R^2 = 0.9842$). With epoch 50, nonetheless, the most accurate model was RNN, indicating that it can increase even more with longer training. CNN performed worse under all scenarios, with higher loss and MAE values, suggesting that it may not be suitable for this specific time series prediction task.

Figure 7.2

Final Results – Actual vs Predicted

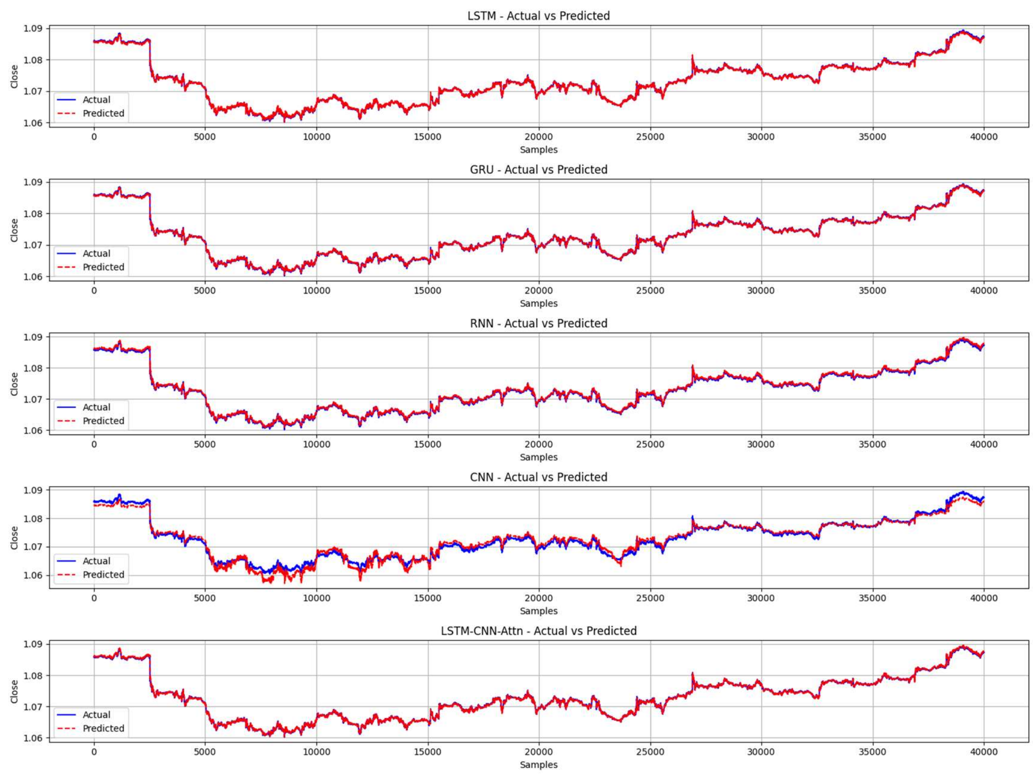


Figure 7.3

Model Performance and Distribution of Prediction Errors in GRU

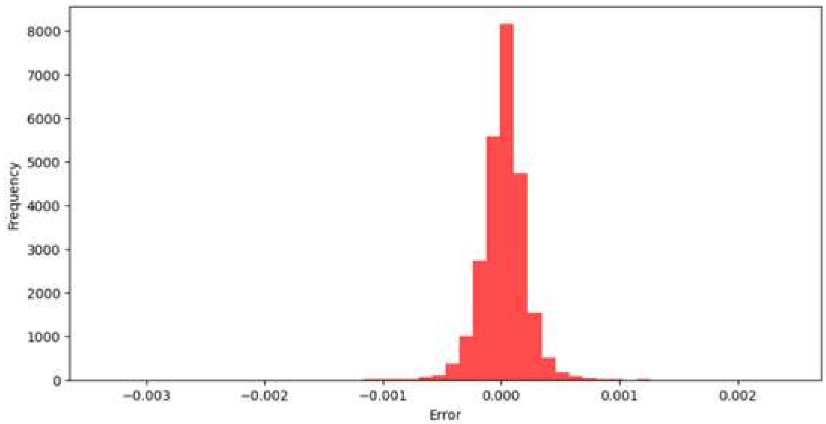


Table 7.1

Comparison of Model performance on the proposed experiment

Rank	Model	MSE	RMSE	MAE	R^2 Score
1	**GRU**	**2.43×10^{-8}**	**0.0001558**	**0.0001069**	**0.9994967**
2	LSTM-CNN-Attn	2.82×10^{-8}	0.0001680	0.0001150	0.9994152
3	LSTM	2.97×10^{-8}	0.0001724	0.0001211	0.9993842
4	Hybrid GRU-LSTM	3.44×10^{-8}	0.0001850	0.0001340	0.9990190
5	GRU (No IR)	9.63×10^{-8}	0.0003103	0.0002620	0.9964330
6	RNN	1.004×10^{-7}	0.0003168	0.0002571	0.9979194
7	CNN	1.2503×10^{-6}	0.0011182	0.0009154	0.9740848

When comparing the performance of different deep learning models for high-frequency Forex prediction, the GRU model performed the best. It had the lowest error values, with an MSE of about 2.43×10^{-8}, RMSE of 0.0001558, MAE of 0.0001069, and an R^2 score close to 0.9995, showing that it predicted the data very accurately. This suggests that GRU is very good at learning patterns in Forex time-series data.

The LSTM-CNN-Attention and LSTM models also gave good results, but they were not as accurate as the GRU. The Hybrid GRU-LSTM model, which combines both types of recurrent units, did not perform better than GRU alone. This shows that adding more complexity does not always lead to better results.

Another important finding came from testing the GRU model without the Impact Ratio (IR) - a feature based on social media sentiment. Without it, the model's performance dropped, with an MSE of about 9.63×10^{-8} and an R^2 of around 0.9964. This shows that including sentiment-based features like the Impact Ratio helps improve accuracy.

Other models like CNN and RNN were less accurate overall, which means models with memory and attention mechanisms work better for this kind of task.

Overall, using GRU models with both technical indicators and sentiment data gives much better results for predicting high-frequency Forex price movements.

CHAPTER 8

LITERATURE REVIEW

Many earlier studies relied mostly on machine learning methods. While some researchers used sentiment analysis of social media content, and some researchers used statistical technical indicators using historical market data. Common machine learning models in Forex prediction include regression, decision trees, trading rules, fuzzy logic, and support vector machines, used widely across different research papers.

This review takes a look at recent trends in machine learning and deep learning methods used to predict Forex markets. This literature review offers a deeper analysis of their applications and the effectiveness of different models. It also analyzes the evaluation methods used in relevant research and conducts a meta-analysis of ML model performance using established metrics, evaluating the accuracy and effectiveness of the combined approach of using social media sentiment analysis, technical indicators, and other relevant data in predicting Forex market trends. Theo goal is to see how well combining social media sentiment, technical indicators, and other data works for predicting market trends. It looks at how effective sentiment analysis is when paired with traditional technical analysis methods.

8.1 The Role of Diverse Data Sources in Forex Forecasting

8.1.1 Historical Data Collection: Tweet Content and Forex Data

The research emphasizes the importance of collecting a comprehensive dataset of tweets from influential financial analysts, Forex traders, and economists who provide insights and analysis on EUR/USD trading in the Forex market. The research focuses on models that consider social media buzz, economic data, and past financial records to get a better idea of currency movements.

Over the past ten years, sentiment analysis and machine learning have come a long way in predicting financial markets. This is especially true in Forex markets, where emotions and quick, high-speed trades play a big role in how prices move. Early foundational work by Bollen et al. [1] established the viability of using social media sentiment for market forecasting, demonstrating that public mood states extracted from Twitter could predict Dow Jones Industrial Average movements with 87.6% accuracy. Their methodology employed lexicon-based tools (Opinion Finder and POMS) to measure six mood dimensions, finding the "Calm" dimension particularly predictive. While focused on equities, this research laid critical groundwork for sentiment-based approaches in other financial markets, suggesting that trader psychology captured through digital platforms could complement traditional technical analysis. However, their reliance on general-purpose sentiment lexicons limited accuracy when applied to specialized financial discourse, a gap later addressed by domain-specific adaptations.

The paper “Foreign exchange currency rate prediction using a GRU-LSTM hybrid network” by M.S. Islam and E. Hossain [2] explore the application of data science techniques in the domain of Forex currency rate prediction. The study focuses on advanced neural network architectures - GRU-LSTM, for time series prediction of Forex currency rates. This involves using data science methodologies to process and analyze historical currency pair data and using this data to train and validate the hybrid neural network model. The study involves data preprocessing, feature engineering, model training, evaluation, and validation, all of which are key components of data science in predictive modeling for financial markets.

The research paper [2] also introduces a new model that combines two popular neural networks for predicting time series: Gated Recurrent Unit (GRU) and Long Short Term Memory (LSTM). The model was tested on EUR/USD, GBP/USD, USD/CAD, and USD/CHF, and its accuracy was checked with different performance measures.

The paper [3] focuses on the comparison of two types of analysis for trading robots, while the [2] paper introduces a novel model based on neural networks for time series prediction in the Forex market.

The research paper of Abednego [3] discusses the development and comparison of two Forex trading robots that use different types of analysis – technical and fundamental. The technical robot is based on the analysis of market prices using tools and indicators in MetaTrader 4 (MT4), while the fundamental robot analyzes Forex-related news and events extracted from a website, www.forexfactory.com. The study aims to evaluate the performance of these robots and determine their effectiveness in generating profits. The technical robot relies on indicators like Simple Moving Average (SMA) and Moving Average Convergence Divergence (MACD) to make trading decisions. However, the paper notes that the technical robot's profitability is not optimal during sideways market conditions. In contrast, the fundamental robot incorporates news reports, economic data, and political events to make decisions based on fundamental analysis. The paper observes that the performance of the technical robot is more stable than that of the fundamental robot. The paper provides an overview of Forex analysis, including technical analysis using candlestick charts and indicators, and fundamental analysis based on economic news and events. It explains the importance of MetaTrader 4 as an electronic trading platform widely used by Forex traders. The experimental setup involves back testing the robots on three currency pairs (EUR/USD, USD/JPY, and GBP/USD) over a 30-day period. The results indicate that the technical robot's performance is stronger and more stable compared to the fundamental robot.

Ahmad and Thet [4] employed a sentiment classification algorithm using a supervised machine learning approach, to analyze tweets related to the US dollar and categorize them as positive, negative, or neutral.

The research [5] conducted by Abednego et al. (2022) explores the integration of sentiment analysis from Twitter data with traditional technical indicators to predict Forex price movements. Emphasizing the significance of market sentiment in trading decisions, the study shows the limitations of relying solely on sentiment analysis and confirms the requirement for a comprehensive approach that includes technical and fundamental analysis. The authors collected historical currency pair data and tweets from Twitter accounts related to Forex news and analysis, using Python libraries such as Tweepy and Snscrape for data retrieval. The sentiment analysis techniques employed, namely TextBlob and VADER Sentiment, provided valuable insights into trader attitudes. The study also acknowledges the importance of combining sentiment analysis with other indicators for more accurate predictions. The researchers have used MetaTrader 4 (MT4) for technical analysis and introduced a robot that incorporates fundamental analysis based on Forex-related news from Forexfactory.com.

The study [5] concludes that the robot using technical analysis demonstrates a more stable and strong performance compared to the one relying on fundamental analysis, particularly in short-term scenarios. This model predicts future closing prices of four major currency pairs: EUR/USD, GBP/USD, USD/CAD, and USD/CHF. This study shows the effectiveness of a hybrid GRU-LSTM model for predicting Forex currency rates. By combining the strengths of both GRU and LSTM networks, the proposed model outperforms existing methods and proves to be a promising approach for navigating the complex changes of the Forex market.

Social media has changed the game when it comes to predicting markets. Twitter, for example, is like a real-time pulse on how people are feeling about the markets. Researchers are now using APIs and natural language processing (NLP) to break down and analyze tweets about big currency pairs, giving us new insights into market trends. When aligned with historical Forex data, this dual-source dataset allows for the exploration of causality and temporal alignment between public sentiment and market behavior [6][7]. These data fusion efforts have yielded richer feature spaces for modeling, capturing latent market dynamics that traditional economic indicators may overlook.

Modern Forex prediction has moved far beyond simple chart analysis. Researchers now use advanced computer systems that can learn from vast amounts of data. Recent research suggests that these new machine learning techniques actually perform a lot better than the traditional statistical methods. For example, one 2023 study found that special computer programs called recurrent neural networks could predict currency movements with 80-90% accuracy, while traditional methods only managed 47-60% [8]. Another 2024 paper showed that combining two powerful techniques (LSTM and XGBoost) works particularly well for unstable currency markets [9]. These new approaches are changing how traders work, with many now using AI tools to help make faster, smarter decisions [10].

Today's systems are different because they can pick up on more than data—they can understand human feelings too. By analyzing social media posts from financial experts, these programs can detect market mood changes before they appear in price charts. This combination of number-crunching and sentiment analysis gives traders a more complete picture of where currencies might be heading.

These references collectively provide a comprehensive overview of different approaches to data collection, data preparation, and data science techniques used in predicting Forex price movements. The literature review can draw from these studies to establish a foundation for understanding the data-related aspects of Forex trading and analysis.

8.1.2 Macro and Microeconomic Indicators

Macroeconomic things like interest rates, inflation, and employment numbers, along with smaller-scale events like company earnings or geopolitical surprises, all play a big role in how currencies are valued. Incorporating these indicators as exogenous variables enhances model robustness by contextualizing price movements within a broader economic framework [12]. Feature engineering practices, including lag transformation and normalization, are employed to harmonize data scales and enhance interpretability.

Good Forex prediction needs to look at the big economic picture too. Studies prove that mixing economic facts with computer models leads to better forecasts. In 2017, researchers created a hybrid system using both neural networks and traditional math models that cut prediction errors below 1% [13]. Another team in 2020 found that including basic economic information like producer prices helped beat simple guessing models [14]. These systems worked because they consider many factors at once - from interest rates to employment numbers - and see how they all connect. It's like putting together a puzzle where each piece is a different economic fact. The more complete the picture, the better the forecast.

The paper “Forecasting Directional Movement of Forex Data Using LSTM with Technical and Macroeconomic Indicators” [11] explores the application of deep learning, specifically Long Short-Term Memory (LSTM), in predicting the directional movement of exchange rates in the foreign exchange (Forex) market. The Forex market, being the largest financial market globally, presents both high risks and profit opportunities for traders. The authors show the distinct characteristics of Forex, such as decentralization, 24-hour operation, and low transaction costs, which differentiate it from other financial markets. The study focuses on the unique challenge of predicting the direction of exchange rates, a requirement specific to Forex. The proposed hybrid model integrates two separate LSTMs, each handling different datasets—macroeconomic and technical indicator data. The experimental results using real data demonstrate the success of the hybrid LSTM model in forecasting directional movement in Forex, incorporating both fundamental and technical analysis techniques. This approach contributes to the growing field of deep learning for time-series forecasting in financial markets.

8.1.3 Sentiment Analysis Algorithms

Bollen et al. [15] used a Naïve Bayes classifier, a well-established machine learning algorithm for text classification, to extract sentiment from news articles related to the stock market.

Hassan et al. [16] investigated the effectiveness of combining sentiment analysis of news articles with technical indicators for Forex prediction. They extracted sentiment scores from news articles using a sentiment classification algorithm, likely a supervised machine learning approach. Their sentiment analysis model achieved an accuracy of 75%. These sentiment scores were then incorporated into a prediction model alongside technical indicators, resulting in a hybrid model that achieved an impressive accuracy of 78% in predicting the daily price movements of the EUR/USD pair. Schumaker and Chen [31] proposed a sentiment analysis approach that uses sentiment lexicons and machine learning techniques to extract sentiment from financial news articles.

Hutto and Gilbert [17] introduced VADER, a rule-based model for sentiment analysis of social media text. The researchers propose a lexicon and a set of rules for determining sentiment polarity, emphasizing the importance of considering context and domain-specific complexities in social media language. VADER is designed to handle sentiment analysis of short and informal text commonly found in social media platforms.

The paper by Hazarika [18] et al. focuses on sentiment analysis using TextBlob, a natural language processing library, for Twitter data. The researchers aim to gauge sentiment polarity from tweets, presenting a method for sentiment analysis in social media. The study is presented in the proceedings of the International Conference on Research in Management & Tech novation.

Deep Learning Models for Stock Price Prediction studies such as [29], [55], [46] and [19] have investigated using deep learning models, including Long Short-Term Memory (LSTM) networks and deep reinforcement learning, for stock price prediction. These models have shown promise in capturing non-linear patterns and dependencies in financial time series data, leading to improved prediction accuracy.

Metaheuristic Optimization Algorithms have been employed to optimize the hyperparameters of deep learning models for stock price prediction by "Stock price prediction with optimized deep LSTM network with artificial rabbits optimization algorithm" [19]. In parallel, the work by [25] uses the cuckoo search algorithm, while [33] explores the role of media sentiment in stock market movements.

Research paper on "Stock Market Prediction Using Machine Learning Techniques" by Nusrat Rouf [20] discusses the methodologies, recent developments, and future directions in the field of stock market prediction using machine learning. The review covers classical and modern approaches for stock market prediction, research methodology, types of data used (market data and textual data), data pre-processing techniques, and machine learning methods used for stock market prediction.

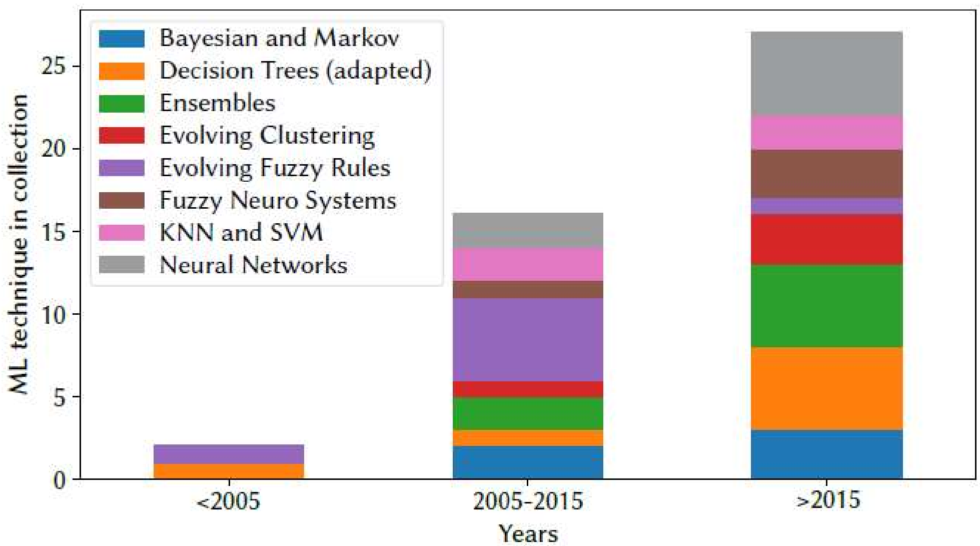
The article "Machine Learning for Financial Prediction Under Regime Change Using Technical Analysis" [21] provides a comprehensive survey of the relevant literature on financial prediction using machine learning. The study looked at how the financial market isn't steady and goes through big changes, especially during crises, recessions, and bubbles. The authors show the challenges of adapting conventional machine learning and statistical approaches to changes in the price-generation process and discuss the growing number of contributions that bridge the gap between data stream learning and economic research.

Some studies examined how to fix the problems when using regular sentiment analysis tools on technical topics. Calefato et al. [22] developed Senti4SD, a supervised machine learning model specifically designed for software development communications, achieving 88.2% accuracy by combining lexical, semantic, and keyword-based features. Their research showed that by manually labeling training data and creating specific features for the task, they could do much better than standard sentiment tools like SentiStrength, which gets about 82.5% accuracy, or the Stanford Sentiment Analyzer with around 85.2%. This finding has important implications for financial sentiment analysis, where market-specific terminology and implicit sentiment expressions require similar domain adaptation. Recent advances in transformer-based models like BERT have further enhanced domain-specific sentiment analysis by capturing contextual relationships in financial text, though their application to Forex markets remains underexplored.

The article [21] addresses the wide range of machine learning algorithms tested in the financial prediction domain and notes that currently, there is no specific dominant technique. The study looked at how technical analysis can help connect two groups - those working on data stream learning and those doing economic research. It also shows that the application of machine learning for financial prediction is still in an early stage.

Figure 8.1

Popular Algorithms used from 2005 to 2015.



Note: Adapted from "Machine Learning for Financial Prediction Under Regime Change Using Technical Analysis: A Systematic Review," by Suárez-Cetrulo, A. L., Quintana, D., & Cervantes, A., 2023, International Journal of Interactive Multimedia and Artificial Intelligence. © 2023 The Author(s).

Sentiment analysis converts qualitative text data into quantitative sentiment scores. Lexicon-based methods (e.g., VADER) and machine learning classifiers (e.g., SVMs, BERT-based models) have shown effectiveness in evaluating financial sentiment from tweets, news articles, and investor forums [23]. These algorithms help quantify the emotional undertone of market discourse, which often precedes or coincides with major price shifts. Recent developments in transformer-based models have improved sentiment classification accuracy, particularly when fine-tuned on domain-specific corpora [24].

8.2 Deep Learning for Forex Forecasting

8.2.1 Explore Relationship

A group of researchers (Said, Omar, and Aziz) developed a hybrid model that combines traditional regression techniques with the cuckoo search algorithm. [25] They constructed their model based on the autoregressive moving average (ARMA) approach, using two years' worth of historical data on USD/EUR currency pairs. To train the model, they experimented with several regression methods, including support vector regression (SVR), multiple linear regression (MLR), CRT regression trees, and partial least squares (PLS). The results from these methods were used as the starting points for the cuckoo search algorithm. Among these, MLR outperformed the others, showing better results than SVR, PLS, and CRT. Overall, their combined approach achieved improved performance compared to any single regression technique on its own. [26] [27]

In another study [28] was introduced by, Paponpat, Kosin, and Nattapol with a different hybrid model that merges statistical analysis with prediction via compressed vector autoregression. They used a random compression method to shrink the huge amount of Forex data into a simpler, more manageable size. After that, they applied Bayesian Model Averaging (BMA) on this compressed data to find out which parameters have the biggest impact. Their model performed well across six currency pairs, surpassing the standard Bayesian Autoregression benchmarks. Similar methods have also been adopted by other researchers [5, 6] to forecast trends in the Forex market.

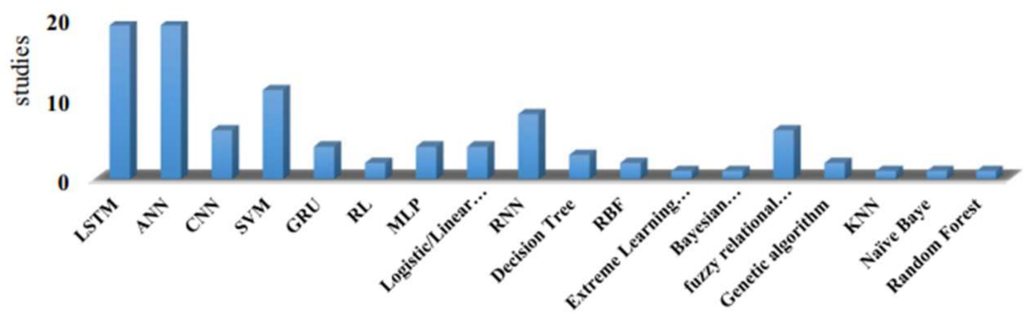
The research [29] suggests that technical indicators and news sentiment can be valuable tools for financial market price prediction. However, no single variable is perfectly predictive, and investors should consider a combination of technical and fundamental analysis to make guided trading decisions. Similarly, in their research, the tweets of the most influential people are used for sentiment analysis instead of news.

The research paper [30] by Ayitey Junior et al. provides a comprehensive examination of the application of machine learning techniques for Forex market forecasting. The study focuses on three key aspects: the machine learning models used, the assessment procedures employed, and the validation approaches used. The research is based on a systematic literature review of publications between 2010 and 2021, analyzing 60 out of 120 papers proposing machine learning algorithms for Forex market forecasting.

The research paper by Ayitey Junior and colleagues [30] examines closely how machine learning predicts the Forex market. It covers three main things: which machine learning models people use, how they test these models, and how they check if the results are reliable. The study reviews a bunch of research from 2010 to 2021, and out of 120 papers on this topic, it focuses on 60 that use different machine learning algorithms for forecasting the currency market.

Figure 8.2

Machine Learning Algorithms used in Forex Research



Note: Adapted from “Forex market forecasting using machine learning: Systematic Literature Review and meta-analysis,” by Ayitey Junior, M., Appiahene, P., Appiah, O., & Bombie, C. N., 2022, Journal of Big Data, 9(1), 1–28. © 2022 The Author(s).

Deep learning models like Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), MLP-Neural Networks, and Radial Basis Function tend to do a better job at predicting the Forex market than simpler algorithms like K-Nearest Neighbors (KNN) and Naive Bayes. The main ways to measure how well they work are MAE, RMSE, MAPE, and MSE. Also, the EUR/USD pair is the most traded currency pair worldwide.

Existing studies on Forex prediction have focused on using either sentiment analysis or technical indicators in isolation. However, there is a growing body of evidence that suggests that combining sentiment analysis with technical indicators can lead to more accurate predictions. The study by Hassan et al. [31] found that a combination of sentiment analysis of news and technical indicators was able to predict the daily price movements of the EUR/USD currency pair with an accuracy of 78%.

The paper “From Text Representation to Financial Market Prediction: A Literature Review" provides [32] provides a comprehensive analysis of text representation methods, sentiment analysis, and information retrieval methods in financial market analysis. The review also explores predictive models and event detection methods, showing the importance of using large amounts of textual data alongside financial market information for investor behavior analysis. The review of investor behavior looks at more than 150 studies in behavioral finance. It focuses on how natural language processing (NLP) and market data are used together to help make financial decisions. The paper discusses what's being done now and what's coming next in text mining and deep learning, especially when it comes to finding patterns, making predictions, and creating advice systems for markets like stocks, cryptocurrencies, and Forex.

Tetlock [33] looks into how the media influences what investors feel and think, and how that affects the stock market. He argues that media coverage of economic and financial news can influence investors' perceptions and expectations, leading to changes in stock prices. Tetlock examines a large sample of media articles and stock market data to analyze the relationship between media sentiment and stock market returns. He finds that positive media coverage is associated with higher stock returns, while negative media coverage is associated with lower stock returns.

The literature review on "News sensitive stock market prediction" by Usmani, S., & Shamsi, J. A. [34] discusses the challenges and opportunities in news-sensitive stock prediction. It covers data preprocessing techniques, feature extraction techniques, prediction techniques, and future directions. Using structured text features really matters more than relying on unstructured or shallow ones. Opinion extraction techniques and domain knowledge are also considered in this study. The paper presents a comprehensive framework for stock market prediction, including the strengths and weaknesses of existing approaches. It identifies three main phases in stock prediction and discusses the challenges and opportunities in each phase. The literature review classifies existing research papers according to different phases in stock prediction. The discussion covers the main ideas and common challenges in predicting stock prices. It also looks at some of the latest methods used to tackle these problems, especially when news sentiment plays a big role in how the market moves.

"Predicting Forex Rates using Sentiment Analysis on Financial Articles" (Danielsson and Gramer) [35] explores using sentiment analysis on financial news articles for predicting Forex rates. It compares different sentiment analysis methods and evaluates their performance in combination with technical indicators. This approach goes beyond the commonly used Twitter sentiment analysis and explores the broader domain of financial news sources. It compares various sentiment analysis methods and assesses their performance in combination with technical indicators, offering valuable knowledge for traders and analysts seeking to use sentiment analysis in their Forex trading strategies.

The research paper on "FinBERT - A Large Language Model for Extracting Information" (Allen H. Huanga, Hui Wangb and Yi Yang) [36] presents a comprehensive approach to predicting future prices of the EUR/USD currency pair by using historical prices and sentiment extracted from financial articles. The authors employ two transformer-based sentiment classifiers, including the existing FinBERT classifier and a newly trained Long former-based sentiment model, to extract mood from the articles. This mood data is then integrated with technical indicators using a stacked LSTM model to forecast the closing price in one hour. The results indicate a 44% improvement in mean absolute percentage error compared to a model that does not consider sentiment from article bodies. The predictive Forex model outperforms a model relying solely on historical prices, showing the value of incorporating sentiment from financial articles in predicting future Forex prices. However, the authors acknowledge uncertainties in the results and emphasize the requirement for caution in quantifying model "goodness." As a result, they refrain from proving the efficiency of the EUR/USD Forex market between October 2020 and May 2021 in the semi-strong form.

Text-based Stock Market Analysis by Fataliyev [37] covers the influence of public and private information on stock market movements, the theories of Efficient Market Hypothesis (EMH) and Random Walk Theory (RWH), and behavioral economics in stock market analysis. The review also discusses the main textual data sources, feature representation techniques, and analysis models used in stock market analysis. The review also shows using different types of textual data sources - news content, social media, micro-blogging data, and data from corporate disclosures. It explores various feature representation techniques for financial time series data, including fundamental and technical analysis, statistical methods, and deep learning approaches.

Figure 8.3

Stock Market Analysis Structure

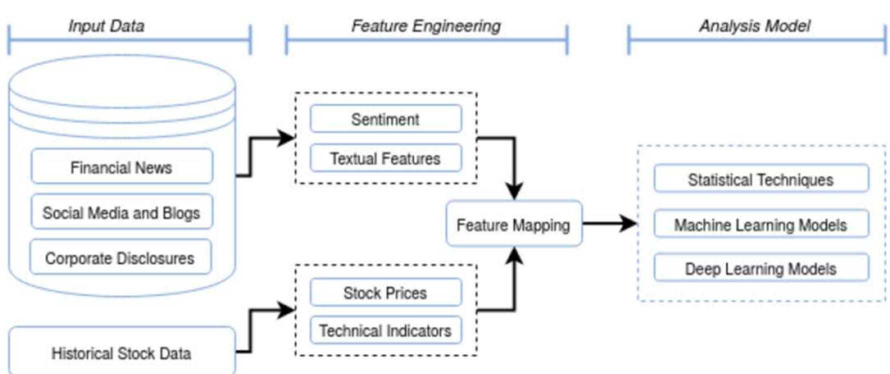
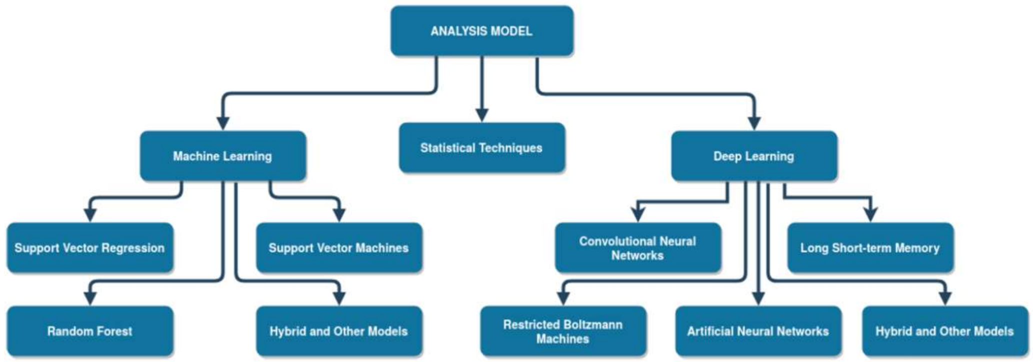


Figure 8.4

Stock Market Analysis Models



Overall, the Sentiment Analysis Algorithm Review provides a comprehensive overview of the literature on this topic, covering various methods and approaches used in the intersection of natural language processing and financial market analysis. The reviews examine the application of statistical techniques, machine learning algorithms, and deep learning methods in stock market analysis.

The development of a long-text sentiment classifier, the introduction of a predictive Forex model (FinBERT-LSIMF), and the evaluation of the model's performance compared to a similar model not using sentiment from article bodies are included in this paper [38]. The results indicate a 72% test accuracy for the long-text sentiment model and a 44% improvement in test loss for FinBERT-LSIMF compared to the model without sentiment.

Advances in deep learning for predicting financial time series have gone hand in hand with improvements in sentiment analysis. Galeshchuk and Mukherjee [39] were among the first to apply deep neural networks specifically to Forex forecasting, demonstrating that multilayer perceptron could achieve 79-82% directional accuracy across major currency pairs. Their systematic evaluation of network architectures and input parameters revealed that optimal prediction windows spanned 20-30 historical price points, with performance varying by currency pair. However, their exclusive reliance on price data overlooked the potential synergies with sentiment indicators, a limitation later addressed through hybrid modeling approaches. Financial data naturally relies on timing, which is why researchers like Nelson and others have turned to special recurrent models that can better handle those time-based patterns. [61] showing that LSTM networks could capture sequential patterns in stock prices more effectively than traditional ARIMA models, achieving 55.9% directional accuracy when incorporating technical indicators as input features. Their research showed how important the right architecture and tuning hyperparameters are when predicting financial time series. But, since their accuracy wasn't very high, it reminded how tough market forecasting is, even with the latest methods.

The relationship between market sentiment, economic indicators, and Forex price movements is inherently nonlinear and temporally dynamic. Correlation and causality tests (e.g., Granger causality) have been used to validate the predictive influence of sentiment on price trends. Researchers have also applied dimensionality reduction (e.g., PCA, t-SNE) to visualize complex interactions among sentiment, technical indicators, and economic data, revealing clusters and anomalies relevant to trading strategies [40]. Correlation and causality tests (e.g., Granger causality) have been used to validate the predictive influence of sentiment on price trends. Researchers have also applied dimensionality reduction (e.g., PCA, t-SNE) to visualize complex interactions among sentiment, technical indicators, and economic data, revealing clusters and anomalies relevant to trading strategies [40].

Trading tools like moving averages and RSI indicators have been used for decades, but do they still work? Recent research gives mixed answers. One 2024 study using advanced computer voting systems (called ensemble methods) achieved 94.8% accuracy in predicting EUR/USD moves [41]. But a 2016 paper warned that many popular indicators might not help much beyond just looking at recent prices [42].

The truth seems to be that some tools work better in certain situations. During calm markets, simple methods might suffice. But when things get volatile, more sophisticated approaches combining multiple indicators tend to perform better. This shows why traders need flexible systems that can adapt to different market conditions.

8.2.2 Develop A Predictive Model

The study by Carapuco et al. [46] introduced a new way to do short-term trading in the foreign exchange market. They built a fake market setup for training purposes, where neural networks with three hidden layers of ReLU neurons are reinforcement learning agents using the Q-learning algorithm. They tested the system thoroughly on the EUR/USD market from 2010 to 2017 and saw an average profit of 74% across different tests and starting points.

The framework incorporates efficient use of historical tick data, providing improved training quality and testing accuracy. The combination of RL and neural networks proves to be effective for generating profitable trading signals in financial markets.

Reinforcement Learning for Stock Selection by Zhang, et al. (2016) [47]: This study proposed a Q learning-based algorithm to predict stock returns. The algorithm incorporated financial indicators as state features and used Q-learning to optimize stock selection decisions. The results demonstrated the superiority of the Q-learning approach over traditional stock selection methods.

Q-Learning-Based Decision-Making for Algorithmic Trading by Huang, et al.[48]: This research focused on applying Q-learning to algorithmic trading strategies. The Q-learning agent learned to make buy/sell decisions based on historical price data and technical indicators. The experimental results showed that the Q-learning agent outperformed benchmark strategies in terms of profitability and risk adjusted returns.

Financial Trading as a Game: A Deep Reinforcement Learning Approach by Moerland, et al. (2018) [49]: This study proposed a deep Q-network (DQN) architecture to predict stock price movements. The algorithm used financial indicators and price patterns as input features and represented the state of the market. The experiments demonstrated the effectiveness of DQN in capturing complex patterns and making profitable trading decisions.

"Q-Learning for Trading in Financial Markets" by Zanjani, et al. (2019) [50]: This research investigated the impact of different state representations on Q-learning performance in stock trading. The study compared various representations, including technical indicators, price patterns, and sentiment analysis. The results indicated that incorporating multiple features led to improved prediction accuracy and trading performance.

Q-Learning with Long Short-Term Memory Neural Network for Stock Execution by Dang, et al. (2020) [51]: This research combined Q-learning with long short-term memory (LSTM) networks for stock execution. The algorithm learned optimal trading strategies based on historical limit order book data and successfully improved execution efficiency compared to conventional trading algorithms.

The article "An Intelligent Fusion Model with Portfolio Selection and Machine Learning for Stock Market Prediction" [52] talks about creating a model that mixes portfolio selection with machine learning to predict how the stock market will behave. The study aims to address the complexities of stock market analysis, and the challenges associated with investment risks. The article discusses the importance of reliable equity market models to enable investors to make guided decisions and reduce the risks of their investment. It shows the potential of trading models to assist traders in selecting the best-paying stocks and reducing investment risks.

In response to the highly correlated nature of stock prices, the study [52] proposes a two-stage framework. In the first stage, the mean-variance approach is used for portfolio construction to minimize investment risk. In the second stage, an online machine learning technique, which is a combination of the "perceptron" and "passive-aggressive algorithm," is presented for predicting future stock price movements. The integration of these two stages aims to use the benefits of both portfolio selection and machine learning to enhance stock market prediction and risk optimization.

The integration of structured (price, volume, indicators) and unstructured data (tweets, news) has led to the development of multimodal predictive models. These systems mix different data sources using methods like combining features and grouping models, which helps make predictions more accurate. Recurrent neural networks (RNNs) and their variants have proven especially effective, as they can model sequential dependencies in time series and sentiment trends [53].

8.2.3 Deep Learning Approaches

Prediction of Forex Rate [54] studies on artificial neural networks (ANNs) in predicting currency exchange rates. The literature review looks at many models including ANN, LSTM, GRU, and other machine learning methods.

The research by Deng, et al. (2016) [55] introduces a novel Deep Reinforcement Neural Network (RDNN) for automated financial asset trading, addressing the challenges of summarizing financial market conditions and fast-changing trading action execution. The RDNN includes a Recurrent Neural Network (RNN) for reinforcement learning and a Deep Neural Network (DNN) for feature learning. Fuzzy learning has been employed for reducing uncertainty in financial data, and the Backpropagation Through Time (BPTT) method handles the recurrent structure. The proposed RDNN trading system is tested on real financial markets, demonstrating strong performance and reliable profits under diverse conditions. The system's contributions lie in its technical-indicator-free approach, allowing automatic feature learning, and the implementation of fuzzy learning in a real-time financial trading context. Future directions include extending the system to handle multiple assets for portfolio management and addressing non-stationary market conditions.

The paper "FINBERT: Financial Sentiment Analysis with Pre-trained Language Models" [56] addresses the challenges faced by sentiment analysis in the financial domain, where existing models often fall short due to domain-specific language complexity and limited labeled data. The authors propose FinBERT, a language model based on BERT, employing transfer learning to adapt to financial sentiment classification. FinBERT outperforms other pre-trained language models like ULMFit and ELMo, achieving impressive results on FinancialPhraseBank and FiQA sentiment scoring datasets. The study explores effective training strategies, including pre-training on financial corpora, preventing catastrophic forgetting through techniques like gradual unfreezing and discriminative fine-tuning. The paper also examines the efficiency of fine-tuning only a subset of BERT's layers, demonstrating that it can provide a favorable trade-off between performance and training time. FinBERT's success shows the potential of pre-trained language models for enhancing sentiment analysis in specialized domains like finance.

The research paper “Deep Learning for Financial Time Series Prediction: A State-of-the-Art Review of Standalone and Hybrid Models” [57] provides a detailed overview of a set of advanced machine learning techniques for financial prediction, focusing on time series. The paper addresses the challenges faced by finance domain experts and professional experts in determining the performance of models, understanding the involved techniques and components, and implementing these models effectively.

The review [48] looks at research from 2015 to 2023, focusing on advanced deep learning models like CNNs and LSTMs, and hybrid approaches that combine CNN, LSTM, attention mechanisms, and other techniques. The authors emphasize how great these models are at capturing spatial and temporal patterns in financial time series data, which helps make more accurate predictions.

The paper [48] makes an important point by showing how recent models can be mapped onto a general framework that includes input, output, feature extraction, prediction, and related steps. It emphasizes that hybrid models like CNN-LSTM and CNN-LSTM-AM tend to perform better than models that rely on just one approach, like a plain CNN. The paper also points out some ongoing issues in predicting financial time series. These include the fact that current methods can be tricky for finance experts to work with, slower prediction times, ignoring some important domain knowledge, a lack of clear standards, and difficulties in generating predictions that are both real-time and high frequency.

The research [58] presents an event-based LSTM framework for price prediction in the Forex Market, combining Elliott Wave Theory and ZigZag indicators to identify optimal trading entry points ("e3"). The authors developed LSTM, BiLSTM, and GRU models trained on selected data around moving average crossovers ("e2"), augmented with 28 technical indicators, achieving superior performance over baseline RNN. This method reduces market noise and improves prediction accuracy.

The paper by Mavale et al. [59] presents a hybrid deep learning approach designed to address the challenges of classifying low-volume, high-dimensional datasets, common in domains like bioinformatics. The authors propose combining deep learning (DL) and traditional machine learning (ML) techniques to improve classification accuracy. The key innovation lies in using a deep neural network (DNN) for feature extraction and then feeding these features into a non-deep learning classifier, such as XGBoost, for final classification. This combined approach takes advantage of both methods: using deep learning to pull out important features automatically, and relying on traditional machine learning models to work well with smaller amounts of data.

The study systematically evaluates the hybrid model across six diverse datasets, including activity recognition (WISDM, HAR), sentiment analysis (Amazon, IMDb, Yelp), and genomic data (Gene Promoter). The results demonstrate that the hybrid model consistently outperforms standalone methods, particularly in scenarios with limited training data. The authors point out that choosing the right layer in the DNN for pulling out features is important. Usually, the earlier layers give better results than the last layer, which is a common trick used in other hybrid methods [59].

Kotios et al. (2022) [60] introduce a hybrid deep learning setup aimed at helping small and medium-sized businesses make smarter financial choices, especially since many are still catching up with digital tech. Their method mixes transaction categorization with cash flow prediction. They use CatBoost to automatically sort transactions into 20 custom groups, and DeepAR, which is based on RNNs, to forecast future money coming in and going out. To deal with uneven data and to make the model's decisions clearer, they include tools like SHAP and LIME for explainability. One of the cool parts of their approach is using surrogate data augmentation — basically creating extra data to train the model better, which really improves the accuracy. The whole process starts with raw banking data passing through some rules, then machine learning sorts out transactions that aren't categorized yet. Those are changed into time-series data for the forecasting model. The DeepAR model is pretty good at catching seasonal patterns and keeps learning online, so it stays current with the latest financial habits and avoids becoming outdated. They show how this setup works well in real-world tasks like budgeting and catching fraud, and they emphasize how important it is for the model to be explainable, both technically and for business decision-making.

Recent progress in combining different deep learning models has boosted how well we can predict time series data, especially in unpredictable areas like finance. A notable example is the work of Gadhi et al. (2023) [60], who investigated the impact of integrating deep learning models with Wasserstein Generative Adversarial Networks using Gradient Penalty (WGAN-GP) to improve the prediction of Brent crude oil price volatility. Their study looked at combined models like ANN with

WGAN-GP, LSTM-ANN with WGAN-GP, and BLSTM-ANN with WGAN-GP. These hybrid setups did better than the usual single models.

This methodology [60] is especially relevant for the FOREX market, where price fluctuations are driven not only by technical trends but also by external factors such as social media sentiment. Long Short-Term Memory (LSTM) and Bidirectional LSTM (BLSTM) networks are particularly well-suited for modeling sequential data with long-range dependencies, common in financial time series. When combined with the synthetic data generation capabilities of WGANs, these hybrid models help mitigate issues related to data scarcity and improve predictive stability under volatile conditions. Adding WGAN-based hybrid deep learning models to FOREX prediction setups - especially ones that include social sentiment and technical indicators—could boost how well we can forecast currency movements.

Combining sentiment analysis with technical indicators is becoming a popular way to make better predictions. Dixon et al. [62] provided a comprehensive framework for such hybrid approaches in financial machine learning, demonstrating that models combining multiple data sources typically outperform single-modality systems. Their analysis emphasized proper validation techniques for financial applications, introducing purged cross-validation to avoid look-ahead bias in time series data - a critical consideration when blending high-frequency price data with potentially lower-frequency sentiment signals. This methodological rigor addresses a key challenge in evaluating integrated models, where traditional validation approaches may yield overly optimistic performance estimates. The theoretical foundations established by Dixon et al. [62] support the development of architectures capable of processing heterogeneous inputs, such as neural networks with dedicated branches for technical indicators and sentiment features.

Looking at the comparison, we can see how the methods and their performance standards have gone through some changes over time. Early neural network applications to Forex prediction, such as the Elman-Jordan recurrent networks used by Kondratenko and Kuperin [63], achieved more modest results (R^2 values of 0.65-0.69) while requiring extensive computational resources. Modern methods often use new design ideas like combining GRU and LSTM to get the right mix of memory and training speed. They also use transformer models for sentiment analysis, which are better at picking up tricky language in financial text. The progression from standalone models (either sentiment or price-based) to integrated systems reflects growing recognition of markets as complex systems where prices emerge from both quantitative factors and collective psychology. This kind of analysis is especially useful for Forex markets, where currency prices often show what people think about the world's economy, along with chart patterns and technical signals.

Critical gaps remain in applying these advancements to Forex prediction. Most sentiment analysis research has focused on stock markets or generic financial texts, with limited attention to the unique characteristics of Forex trader discourse. Currency trading is really fast-paced and can be intense, which means that how people feel about it—like their opinions on social media, can have a bigger impact compared to other markets. Also, not many studies have looked into how feelings and currency prices move together over time—whether social media chatter comes first, reacts afterward, or if they change together at the same time across different periods. The optimal methods for fusing sentiment features with technical indicators also require further investigation, particularly whether early (feature-level) or late (prediction-level) integration yields better performance in Forex applications.

Recent progress in transfer learning and multimodal systems gives us some promising ways to tackle these challenges. Pretrained language models like BERT can be fine-tuned on Forex-specific corpora to improve sentiment classification accuracy, while attention mechanisms may help identify the most predictive temporal relationships between sentiment and price movements. Ensemble approaches that combine the strengths of different architectures - such as CNNs for local pattern detection in sentiment trends and LSTMs for sequential price dependencies - could further enhance prediction robustness. However, these techniques must be evaluated against the practical constraints of real-time trading systems, where latency and computational efficiency become critical factors alongside accuracy metrics.

The literature collectively establishes several key principles for Forex prediction systems: (1) domain adaptation is essential for accurate sentiment analysis in financial contexts, (2) deep learning architectures outperform traditional statistical methods for both sentiment classification and time series forecasting, (3) hybrid models combining multiple data modalities generally achieve superior results to unimodal approaches, and (4) proper validation methodologies must account for the unique characteristics of financial time series. These findings help create a combined Forex prediction system that uses the latest in natural language processing and deep learning. It's designed to tackle the unique challenges of currency markets.

Deep learning architectures like Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs) have become standard tools in time-series forecasting due to their ability to retain long-term dependencies and manage vanishing gradients [64]. Recently, hybrid models like CNN-LSTM, GRU-BiLSTM, and attention-based transformers have shown better results by combining different design strengths. These approaches not only make predictions more accurate but also help prevent overfitting thanks to regularization and dropout methods [65][66].

The newest Forex prediction systems are getting incredibly fast and accurate. In 2024, researchers built a model that makes predictions every 2 seconds - fast enough for super-quick trades [43]. Other teams have found that letting computer programs automatically combine different strategies often works better than any single approach [44].

For predicting how wild price swings might get, different tools work best for different time frames. Short-term volatility is best predicted by LSTM networks, while older statistical methods still work well for longer-term forecasts [45]. This shows that even with all the new technology, sometimes blending old and new methods gives the best results.

CHAPTER 9

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9.1 The Role of Diverse Data Sources in Forex Forecasting

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