Integrating Sentiment Analysis into AI-Driven Budgeting: Advancing Personal Financial Management through Emotion-Aware Financial Insights

Natural Language Processing - Sentiment Analysis

MSc Research Project

Artificial Intelligence

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MSc Project Submission Sheet
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Module:	Msc. Research Practicum		
Supervisor:	Lavish Thomas		
Submission Due Date:	11-Aug-2025		
Project Title:	**Integrating Sentiment Analysis into AI-Driven Budgeting: Advancing Personal Financial Management through Emotion-Aware Financial Insights Natural Language Processing - Sentiment Analysis**		
Word Count:	***6895***		
	Page Count 20		

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Integrating Sentiment Analysis into AI-Driven Budgeting: Advancing Personal Financial Management through Emotion-Aware Financial Insights

Natural Language Processing - Sentiment Analysis

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Abstract

This study aims to integrate sentiment analysis models within AI-driven budgeting systems to enhance emotion-aware financial guidance. Methods involved embedding Random Forest, AdaBoost, Deep Neural Network, and LSTM classifiers into a budgeting framework, with TF-IDF vectorisation for machine learning models and tokenisation with embedding's for deep learning models on a balanced dataset of financial news headlines. Findings indicate that the LSTM model achieved the best balance of precision and recall across bearish, bullish, and neutral sentiments, while the Random Forest classifier delivered high precision but low recall for minority classes, AdaBoost underperformed, and the Deep Neural Network yielded moderate improvements. Limitations include vulnerability to class imbalance, misclassification of sarcasm and domain-specific jargon, and high computational requirements for training. Future research should explore transformer-based architectures with domain-adapted embedding's, adaptive sampling techniques, and sarcasm detection modules to improve accuracy and efficiency. Integration confirms sentiment signals can be effectively mapped into budgeting rules.

Keywords: Sentiment analysis, AI budgeting, LSTM, Financial forecasting

1 Introduction

Financial Sentiment Analysis (FSA) can be termed as a study field that fundamentally analyses investors' sentiment from financial news, measures and quantifies the sentiment of investors from financial textual sentiment (Du et al., 2024). According to Jin, Chen, and Yang (2024), higher variance within the financial news intensity is fundamentally linked with higher economic uncertainty. In this regard, potential investors strictly followed financial news to understand the market sentiment using different investment applications. More than 7 in 10 people with smartphones manage their finances using an app each month. The market value for personal finance mobile apps was USD 17.75 billion in 2024 and is forecast to expand to nearly USD 95.6 billion by 2032 (Nandi, 2025). Similarly, 72% of people in the U.S. felt worried about finances at least once during the previous month, according to a 2023 survey from the American Psychological Association (Gallo, 2023). Traditionally, budget planning depends on reports of transactions and numbers, skipping over the emotional aspect of why people spend as they do. Similarly, the market for sentiment analysis software is showing great growth and is projected to rise from US$5.1 billion in 2024 and is projected to US$11.4 billion by 2030 at a CAGR of 14.5% (Business Wire, 2025). In this context, the development of a stock market sentiment (bearish, bullish, or neutral) prediction model based on financial news can allow investors to make strategic investment decisions. This study seeks to leverage Natural Language Processing (NLP) techniques along with Machine Learning (ML) and Deep Learning (DL) algorithms to accurately predict stock market sentiment based on financial news.

Despite the rapid growth of AI-driven personal budgeting tools, current systems are constrained by an exclusive focus on quantitative transaction metrics, failing to capture investors' emotional contexts that significantly influence the spending behaviour of stock market investors (Gamage et al., 2024). Present platforms (like eToro, DEGIRO) fail to analyse market sentiment in real time, so they fail to predict the market sentiment (bearish, bullish, or neutral) when users are anxious about their investment in the stock market. In this context, by joining sentiment analysis with budgeting algorithms, this research helps detect and interpret emotional clues in the financial news. As a result, the framework can make budget advice more relevant to users' investment emotions, making them more likely to follow it and stick with it. Moreover, to help users manage money concerns fully and avoid the challenges of stress, this study focuses on the development of ML and DL algorithms for predicting stock market sentiment based on the release of financial news.

The study aims to incorporate sentiment analysis models into AI-powered personal budgeting systems using innovative ML, DL, and LSTM methods to track real-time investor opinions from finance texts and social media platforms.

The objectives of this research are as follows:

- To apply the implements of sentiment analysis models (ML, DL, and LSTM) into AI-based budgeting budgets with an objective of improving by at least 5-10% the classification efficiency and F1 score of minority or bearish and optimistic classes on a par with baseline ensemble techniques.

- To compare and understand the performance of Random Forest, AdaBoost, DNN, and LSTM to identify sentiments in market in real time with a recall rate of more than 0.50 on the minority classes to lower false negativity in a market sentiment detection.
- To derive and rationalise budgeting strategies that can transform sentiment outputs into financial suggestions, with the view of increasing the level of personalised advice adherence rates, which may be identified by closeness between users and their emotions.

The research question that this research has answered is stated below:

- How can sentiment analysis enhance AI-powered budgeting tools by analysing consumer emotions in financial transactions and reviews to improve personalised financial recommendations?

Null Hypothesis (H_0): The use of sentiment analysis with ML, DL, and LSTM models in AI-based personal budgeting systems does not impact the accuracy or efficacy of fiscal management results.

Alternate Hypothesis (H_1): The incorporation of sentiment analysis with ML, DL, and LSTM models in AI-powered personal budgeting applications enhances the precision and efficiency of fiscal management results.

The rationale for doing this research on the basis of budgeting behaviours which often changes with people's moods, but most AI-based budgeting tools, such as Mint and Pocket Guard, focus solely on numerical data, overlooking the emotional context behind spending decisions. Using feelings and emotions in budgeting by reading users' unorganised data, such as what they write in financial transactions or on social networks, can make recommendations that motivate people to meet their financial goals. This hybrid approach promises to enhance user engagement, promote healthier spending habits, and mitigate decision fatigue by aligning financial advice with emotional contexts. In addition, by integrating classical ML classifiers (e.g., Random Forest, AdaBoost) with DL architectures such as DNN and LSTM to extract and model emotional cues from transaction narratives and social media texts, the system can more accurately interpret sentiment dynamics, thereby delivering clearer, more trustworthy AI-driven budgeting recommendations (K. Kirtac and Germano, 2025). As a result, the research aims to bring together emotion-aware analytics and AI in budgeting, so that investors can receive genuinely tailored advice based on their changing emotions and manage their finances well into the future. Similarly, the **significance** of this research seeks to fill an important gap in personal finance by adding emotion detection directly to AI-controlled budgeting software. State-of-the-art frameworks such as Emotion AWARE demonstrate robust, adaptable, and explainable multi-granular emotion detection capabilities in diverse domains (Gamage et al., 2024). Targeted aspect-based emotion analysis has been applied to financial Twitter messages for market insights. The novel contribution lies in a way to combine advanced emotion-analysing models (for example, domain-adapted transformers) with real-time oversight systems to translate emotions within transaction narratives, shared posts, and personal diaries into instant, personalised suggestions (García-Méndez et al., 2023). Financial reminders are more engaging, nudges become emotionally supportive, and people are encouraged to budget sustainably. This work helps explain how emotions are processed in financial systems and gives rise to new, people-oriented financial tools.

2 Literature Review

Financial news and the publication of company reports play a pivotal role in the growth of investor confidence, which fundamentally drives stock market sentiment. In this context, the study by Gupta, Devji and Tripathi (2025) undertakes a comprehensive exploration of the role of digital proxies in capturing investor sentiment and its impact on stock-market performance. Methodologically, Gupta, Devji and Tripathi (2025) conduct a systematic literature review of 108 peer-reviewed studies, categorising them by data sources (news, social media), analytical frameworks (OLS, GARCH, Machine Learning, Deep Learning, LLMs) and geographic focus. The obtained results indicated that digital proxies (such as Google Trends, Twitter feeds, and news headlines) exhibit higher predictive accuracy for short-term market movements compared to traditional sentiment indices (like market volatility) (Bollen, Mao and Zeng, 2011). However, limitations of this study include reliance on secondary sources prone to publication bias, a focus on studies published only through early 2025, and a lack of empirical validation for LLM-based models in live trading environments (Fan, Tan and Wang, 2020; Li et al., 2022). Similarly, the study by Kamath et al. (2024) explored the influence of investor sentiment on Indian equity markets by constructing an index reflecting sentiment (INDex) and measuring its impact on the Nifty 500 and five sectoral indices (Automobile, Information Technology, Metal, Fast-Moving Consumer Goods, and Public Sector). The methods use seven measures that are indirect indicators like trading volume, money entering mutual funds, Volatility Index (VIX), put–call ratio, and selected macroeconomic variables like GDP, inflation, and apply Principal Component Analysis (PCA) to build the INDex (Kumar and Rao, 2019; Barber and Odean, 2008). Following this, the study by Kamath et al. (2024) executed an ordinary least squares

(OLS) regression using monthly data from 2010 to 2020 to find out the link between the INDex and the returns of the index. Findings of this study revealed that there is a strong link between the sentiments people give and stock returns, and metal shares are the most reactive ($\beta = 0.189$), while FMCG ($\beta = 0.109$) shows the least responsiveness in the Nifty 500. However, within this study, proxies (like investor confidence, market sentiment) used might not fully represent retail investor sentiment, and linearity is assumed. Thus, structural changes and non-linear patterns are not considered (Chongsiriwat, Schmitz and Shukla, 2021; Chagué, 2023).

On the contrary, the study by Cristescu et al. (2023) investigates how financial-news sentiment extracted from titles and descriptions correlates with stock-price movements of Microsoft, Tesla, and Apple. This study utilised TextBlob to compute polarity scores for news headlines and article descriptions published daily, followed by Pearson correlation, linear regression, and continuous wavelet coherence analyses to uncover temporal dependencies. Findings outlined that title-level sentiment has a stronger contemporaneous correlation with Tesla's opening prices, whereas description-level sentiment more closely tracks Microsoft's opening prices (Tetlock, 2007). Therefore, it can be stated that financial news sentiment materially influences market sentiment and stock-price behaviour. The release of negative news related to stocks creates a factor of nervousness among investors, which negatively affects market sentiment (Barunik et al., 2020).

Emergence of ML and DL, along with NLP techniques, plays a significant role in predicting market sentiment. Correia, Madureira and Bernardino (2022) seek to analyse how Deep Neural Networks (DNNs) can extract and integrate sentiment information from social media with stock-market data, aiming to boost forecast accuracy. Correia, Madureira, and Bernardino (2022) design a DNN framework that works with unstructured texts like tweets and fields of structured data, by using convolution for pulling out relevant features and LSTM for grasping time-based relationships. On multiple datasets annotated with emotion, this study revealed that convolutional models are superior for complex and noisy text, and LSTM layers ensure contextual recall, getting over 73% of training accuracy and 69% testing accuracy on simulations for sentiment-investment. This indicates that the obtained accuracy of the Deep Neural Networks model was moderate, which can be a limitation of this study. However, limitations are that the model may be too complex for practical use, it needs extensive hardware for training, and its performance drops when social media language becomes very sarcastic or jargony (Zhang et al., 2020).

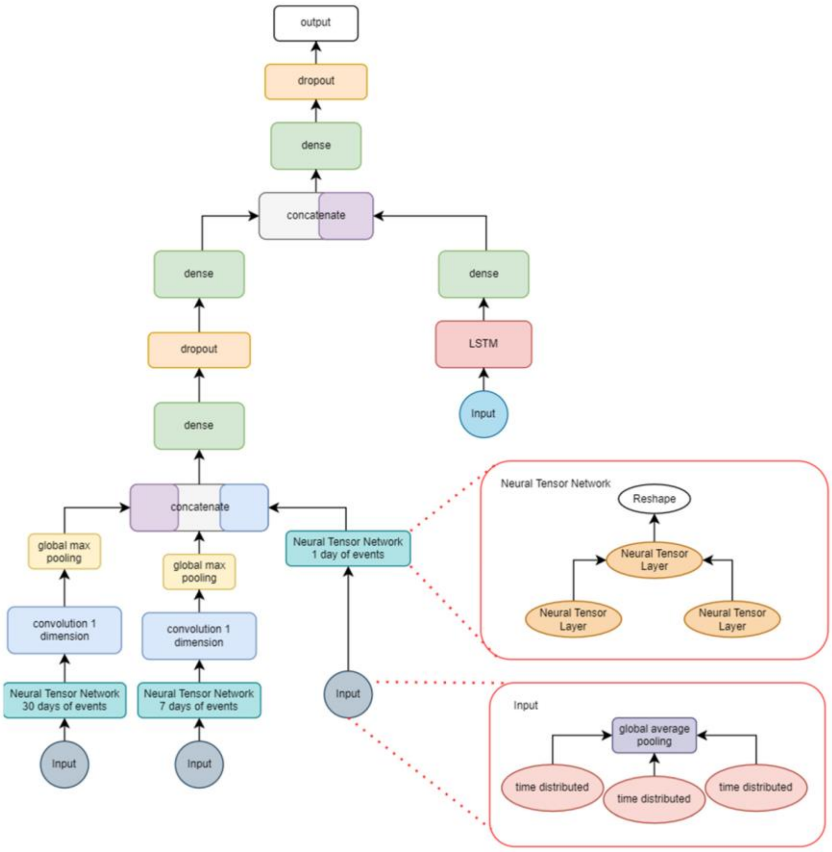

Figure 1: DNN architecture for stock market sentiment analysis

(Source: Correia, Madureira and Bernardino, 2022)

On the contrary, Chandra and Mondal (2025) conducted a careful study using machine learning (ML) for sentiment analysis in forecasting the stock market, looking for ways to understand various trends, datasets, and open questions in this field between 2018 and 2023. This study goes through more than 50 independent studies, arranges them by the algorithms being used (SVM, Naïve Bayes, Logistic Regression, Random Forests, Neural Networks), and uses data sources (Twitter, StockTwits, feeds of financial news). Results from these studies show that traditional ML approaches are only moderately accurate (60%-75%) using n-gram and TF-IDF features, but deep learning models (CNNs, LSTMs, hybrid architectures) consistently get better results and outperform classical classifiers when they use pretrained embeddings or attention mechanisms (Devlin et al., 2019).

On the contrary, Muhammad et al. (2024) propose an explainable Deep Learning framework for multi-class stock-market trend prediction, implicitly underscoring the role of textual sentiment as a key feature among other technical indicators. Within this study, both raw time-series data and sentiment-scored input derived from financial news headlines were analysed using a Deep Neural Networks (Recurrent Neural Networks) architecture with explainability via SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic

Explanations) to reveal feature importance (**Figure 2**). Findings on diverse global indices (such as S&P 500, DAX 30, Nikkei 225, FTSE 100) indicated that the DL model achieves exceptional trend-classification accuracy of 94.9%, markedly surpassing traditional ML benchmarks (Random Forest (85.7%), SVM (60%)). However, despite these strengths, limitations include an overreliance on lexicon-based sentiment scoring (which struggles to capture nuanced or sarcastic language) (Lundberg and Lee, 2017; Hutto and Gilbert, 2014).

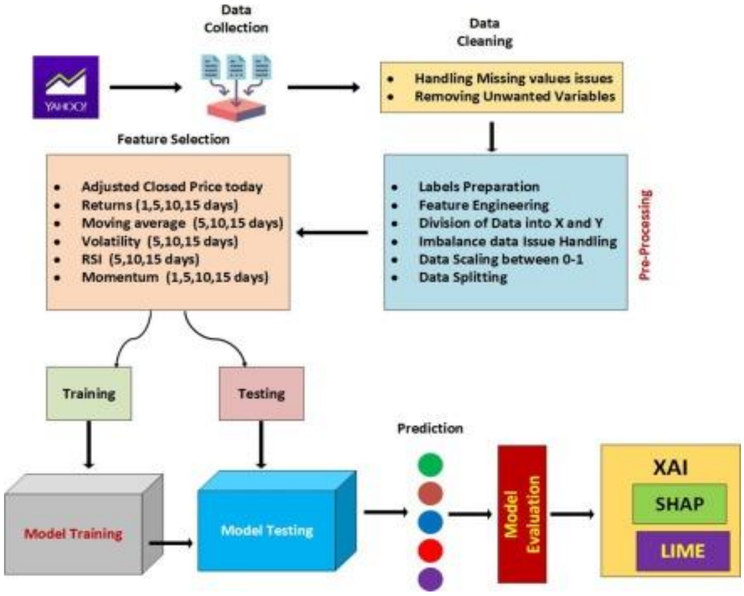

Figure 2: Methodological flow for predicting stock market sentiment.

(Source: Muhammad et al., 2024)

Based on the discussion, ML and DL techniques have the capability to capture stock-market sentiment by capturing complex, non-linear patterns in financial news, which allows investors to make strategic investment decisions. This allows investors in the stocks, which can provide them with the optimal market returns and allow balancing the trade-off between returns and investment risks.

Firms can restructure their financial strategies according to the market sentiment and investment opinions in the market with sentiment-based budgeting. Gathering and using employee opinions, customer responses, online chatter related to stock market trends and company performance, and employee surveys in budgeting leads to better ways of managing resources. According to Barbaglia et al. (2024), if both employee morale and customer experiences are falling, managers can use the budget to boost employees, improve training, or improve levels of service. Moreover, according to Mun and Kim (2025), a surge of positive feelings from the market may call for a rise in spending on new development projects or advertising campaigns. Doing so balances the budget to keep up with changing attitudes and prevent budget problems.

Moreover, sentiment-based budgeting fosters initiative-taking, risk management, and scenario planning. According to Koesoemasari et al. (2022), firms can incorporate sentiment signals into forecasting models to adjust contingency reserves, which leads to setting aside larger buffers when sentiment turns pessimistic and allowing for lowering the reserves when sentiment stabilises. Therefore, it can be stated that this approach can support diversification strategies, such as identifying sectors, departments, or product lines with consistently positive sentiment can guide capital deployment into high-potential areas, whereas persistently negative sentiment may trigger budget cuts or restructuring.

This study employs various Machine Learning (ML) and Deep Learning (DL) classifiers to optimise the performance of sentiment analysis in AI budgeting. The models selected compromise between interpretability, performance, and the capacity to process text-based fiscal data effectively.

Random Forest Classifier: It provides robust classification by aggregating decision trees to mitigate overfitting (Zhang et al., 2022). However, it might not manage a high computational expense and is liable to perform less efficiently on unstructured and noisy financial textual information (Du and Zhai, 2024). RF classifier is suitable for handling high-dimensional fiscal text features with interpretability.

AdaBoost Classifier: It improves weak classifiers iteratively to enhance prediction accuracy (Syed Safdar Hussain and Syed, 2024). Yet, it is not robust to noisy data and outliers that may diminish accuracy with texts that are sentiment-cluttered, such as financial texts (Hornyák and Iantovics, 2023). It is quite strong in capturing subtle sentiment variations pivotal in financial text.

Deep Neural Networks (DNN): It identifies complex patterns with several underlying layers for high prediction accuracy (Mienye and Swart, 2024). However, DNNs are demanding numerous data variants and processing power, which could make them hard to train in niche financial sentiments (Ahmed et al., 2023). DNN is therefore ideal in modelling the complex financial sentiment-budgeting behaviour relationship.

Long Short-Term Memory (LSTM): LSTM is well-suited to learn sequential relationships in text, which is crucial in sentiment detection (Murthy et al., 2020). But LSTM models take time to train, and it is easy to overfit when the amount of financial text data is small or irregular (Albeladi, Zafar, and Mueen, 2023). It is well-suited for sequential tweet data processing for the detection of sentiments that determine financial decisions.

Concepts of the **Dual Process Theory** have been applied in this study to evaluate the significance of financial news sentiment on the stock market trends. According to Kahneman

(2011), Dual-Process Theory posits that two distinct cognitive systems are System 1 (which is characterised by rapid, intuitive, and automatic processing) and System 2 (marked by slower, analytical, and effortful reasoning), leading to shaping investment decisions (**Figure 3**).

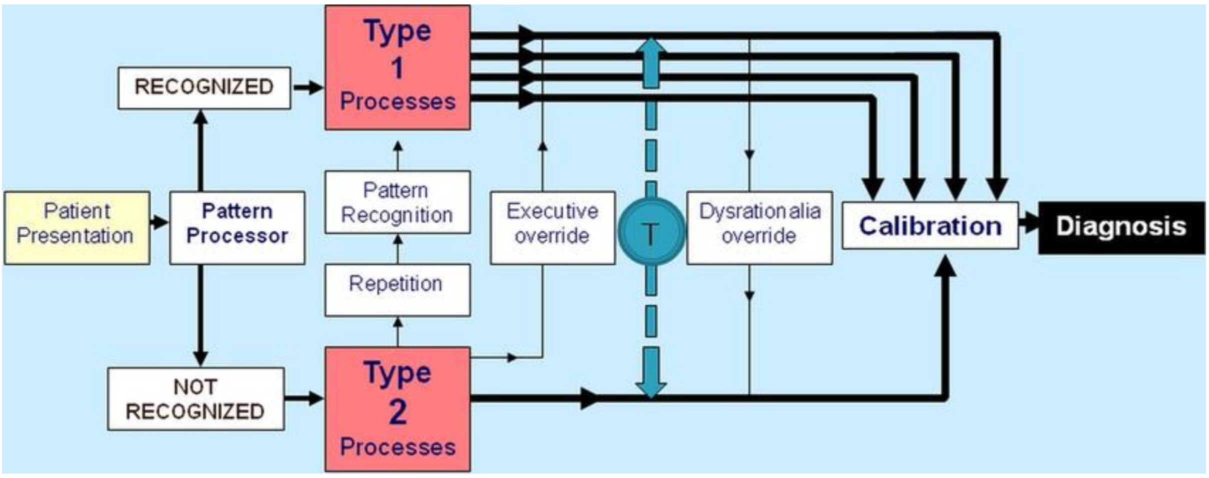

Figure 3: Dual Process Theory

(Source: Croskerry, Singhal and Mamede, 2013)

Relying on emotions (System 1) can cause potential investors to implement budget changes quickly, whereas taking time to analyse (System 2) signals helps them look at the trends with data and plan better budgets that address several challenges and suit different situations. Therefore, it can be stated that the incorporation of Dual Process Theory can allow evaluation of the sentiment of investors and its potential impact on market trends.

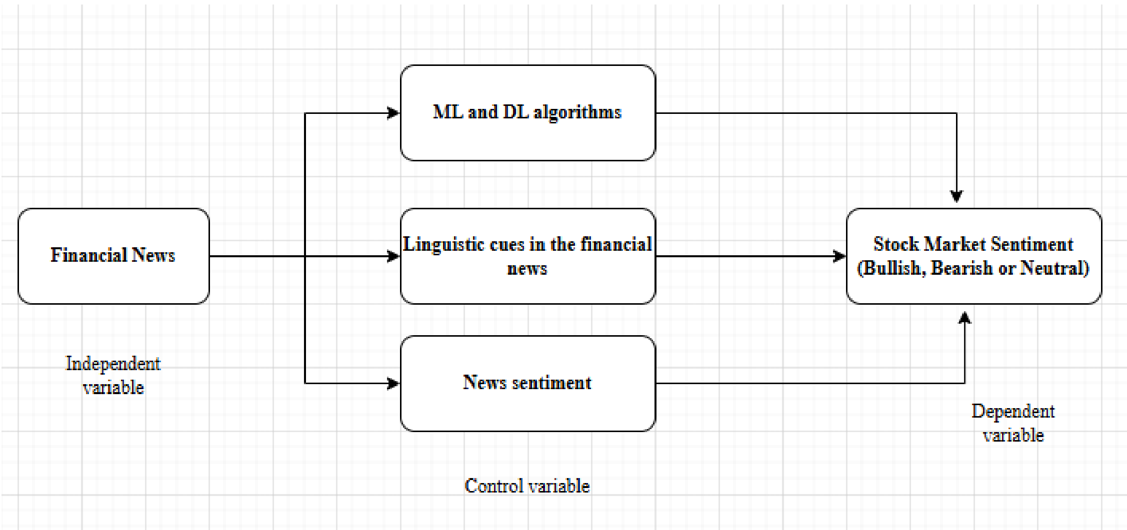

Figure 4: Conceptual Framework

Past literature has focused on the evaluation of the importance of sentiment analysis of financial news on overall stock market trends. The studies by Correia, Madureira and Bernardino (2022) and Chandra and Mondal (2025) developed ML (SVM, Random Forest, Logistic Regression) and DL algorithms (such as LSTM) and has achieved accuracies of less than 80%, indicating potential gaps in developing an exceptionally accurate predictive model for predicting market trends based on financial news (Schumaker and Chen, 2009). Moreover, limited focus has been maintained on developing predictive models on financial news for predicting stock market trends, underscoring a potential gap in past literature. In this regard, this study seeks to bridge the gaps through developing both ML and DL models based on financial news to predict market sentiment (bullish, bearish, or neutral).

3: Methodology

The research follows a ***deductive research approach***, starting with proven theories of sentiment analysis, behavioural finance, and AI-based budgeting. The deductive method facilitates systematic hypothesis testing, enabling the study to systematically evaluate the connection between features by quantitative analysis (Fife and Gossner, 2024). Using predetermined models on secondary quantitative data like financial transactions, sentiment-tagged texts, and market indicators, the research ventures to prove existing hypotheses about how emotional cues affect the accuracy of budgeting. The approach is well-suited to quantifying the extent to which emotion-sensitive financial knowledge, achieved by natural language processing, contributes to personal fiscal management precision and decision-making consistency.

The research in this study follows a ***positivism research philosophy***, focusing on objective examination and quantifiable outcomes from secondary quantitative information. Positivism underpins the structured as well as rigorous approach to relying on objectives, data, and methods to derive predictions (Park, Konge, and Artino, 2020). By isolating itself to observable, measurable facts, positivism removes subjective bias, guaranteeing the dependability and reproducibility of findings. The use of positivism enables systematic analysis to determine how sentiment analysis, via natural language processing, objectively helps to improve AI-based budgeting models, thus facilitating improved personal financial control using scientifically proven, emotion-sensitive financial advice.

An ***exploratory research design*** is used to examine how the incorporation of sentiment analysis into artificial intelligence-based budgeting can improve personal fiscal management. While grounded in secondary quantitative data, this research delves into new connections between emotional sentiments and financial behaviours that have not been thoroughly investigated, which in case is analysed through ML and DL models. The exploratory research design provides the flexibility of unearthing intricate patterns in large-scale datasets to explore the significant data patterns (Saka, Chinagozi, and Joe, 2023). The exploratory design facilitates the revelation of insights yet to emerge, informing the future construction of emotion-sensitive budgeting models. It allows the detection of new variables that have not been monitored, underpinning greater insight into how natural language processing can revolutionise financial decision-making.

This research employs a ***secondary quantitative research strategy,*** using available datasets that include financial transactions, sentiment-tagged text, and emotional measures (bearish, bullish, or neutral) derived through natural language processing. The secondary quantitative research strategy provides access to large, organised data sources, enabling statistical examination of the correlation between features present in the data (Lim, 2024). Secondary data utilisation ensures cost savings, timely availability of large sample sizes, and increased generalizability. The quantitative strategy also enables objective measurement of emotional impacts on financial behaviour with empirical proof to support how sentiment analysis contributes to AI-based personal fiscal management by using emotion-sensitive insights.

The dataset is derived from a publicly available authentic platform, named Kaggle, which is consistent with the research aim of incorporating sentiment analysis into AI-budgeting. The dataset consists of 11,932 finance tweets, which are classified into three sentiment classes such as Bearish (LABEL_0), Bullish (LABEL_1), and Neutral (LABEL_2) (Kaggle, 2024). These affective labels serve as the target variable in this study, reflecting the user's emotional reaction towards financial news, hence leading to appropriate investment and budgetary decisions. The data, acquired by accessing the Twitter API, is live public opinion on financial markets and is thus highly pertinent to exploring the influence of emotional signals on personal financial decision-making.

The data are separated into 9,938 training examples and 2,486 validation examples, allowing model creation and performance measurement for sentiment classification. As financial behaviour is subject to public perception, these labelled tweets provide a strong basis on which Natural Language Processing (NLP) can be implemented. This information enables machine learning models to be trained so that they can make predictions for sentiment correctly, and this can subsequently be integrated with budgeting algorithms to adjust recommendations for money based on present emotional trends.

4: Design Specification

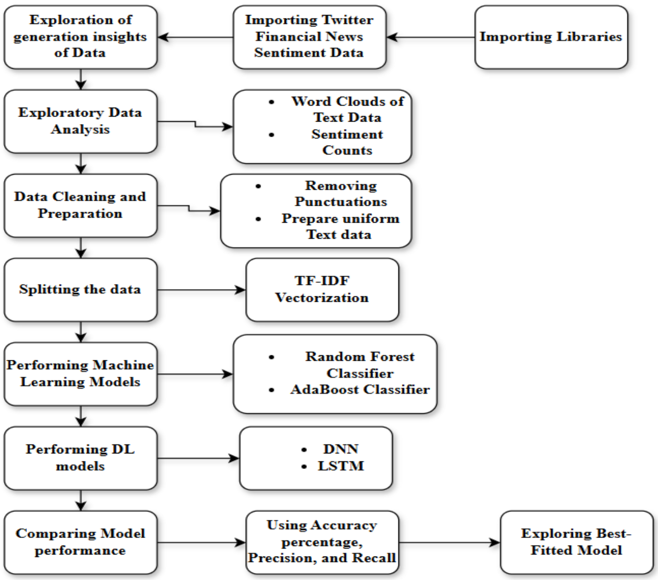

Figure 5: Proposed Methodological Architecture

The analysis starts by importing libraries and importing the ***Twitter Financial News Sentiment Dataset [Refer to Figure 5]***. Word clouds and counts of sentiment are created using initial exploratory data analysis. Cleaning of data strips out punctuation and normalises text, followed by TF-IDF vectorisation to transform text into numerical features. Splitting the dataset into training and testing sets is performed. Machine learning models (Random Forest, AdaBoost) and deep learning models (DNN, LSTM) are used to predict sentiments. Model performances are measured with accuracy, precision, and recall, enabling the selection of the best-suited model for emotion-based AI-driven budgeting insights (Lathe 2025).

5: Implementation

5.1 Libraries and Data Loading

Figure 1 (appendix) depicts the bottom-line configuration of introducing sentiment analysis to artificial intelligence-based budgeting systems. The figure shows how crucial libraries (TensorFlow, sklearn, pandas, and SMOTE) need to be imported to accomplish relevant preprocessing data and model formulation, as well as text analysis. It is also demonstrating how training data and validation data are successfully loaded in their respective datasets, where each row of the training data and validation data shows financial news headlines with alternative sentiment categories (labels) attached to them. This step makes machine learning outputs dependable by checking the data structure, shape, and content. This data, labelled with such sentiment, is critical to constructing the emotion-sensitive financial model to have a more natural and responsive personal budgeting tool according to the sentiment.

5.2 Data Cleaning and Preparation

Key data validation and preprocessing activities improve the model's performance in emotion-based financial advice and are depicted in **Figure 2 (appendix)**. Checking and managing null and duplicate values helps to ensure data consistency and enhance predictive accuracy (Ali, Emran and Asmai, 2021). It also verifies that there is no Null and duplication in the training and validating datasets, making the data dependable and complete. Also, the figure introduces a superior text clean-up capability that uses filters for the elimination of URLs, punctuating marks, numbers, and whitespaces annotation for standardising financial text input. This preprocessing plays a key role in the accurate extraction of the sentiment behind the financial news headlines. Clean text builds a solid background for ML models, which enhances the accuracy of sentiment-based budgeting tools in personal fiscal management systems.

5.3 Exploratory Data Analysis

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9543 entries, 0 to 9542
Data columns (total 3 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   text        9543 non-null   object
 1   label       9543 non-null   int64 
 2   clean_text  9543 non-null   object
dtypes: int64(1), object(2)
memory usage: 223.8+ KB

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2388 entries, 0 to 2387
Data columns (total 3 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   text        2388 non-null   object
 1   label       2388 non-null   int64 
 2   clean_text  2388 non-null   object
dtypes: int64(1), object(2)
memory usage: 56.1+ KB
```

Figure 6: Checking Data Types of Features

The inspection of data types and non-null data entries is outlined in **Figure 6** across the training and validation datasets. This validation process makes sure that the label column is typed as int64 to perform a classification-type task, and text and clean_text columns are typed as objects that are used by the text-based process. Ensuring compatible data types among the datasets is necessary to ensure that the data can be seamlessly integrated into ML models to boost the accuracy of personal budgeting AI-based tools.

Word clouds, in which the most important terms characterising the ***bearish, bullish, and neutral*** sentiment are presented. Active words in these representations include fall, drop, and loss in terms of Bearish sentiment, strong, growth, higher, raised in terms of Bullish sentiment, and stock, marketscreener, and deal in terms of neutral sentiment, providing an informal understanding of sentiment-induced language when headlining financial linguistic representations. This assists in discovering emotional clues and common financial terms that are based on market trends. With the knowledge of these sentiment-specific keywords, the rules that need to be used by the AI-powered budget system to classify a given input or news piece by a user can be provided and eventually result in more embracing and emotion-sensitive financial analysis when the user is trying to make a personal decision regarding their budget.

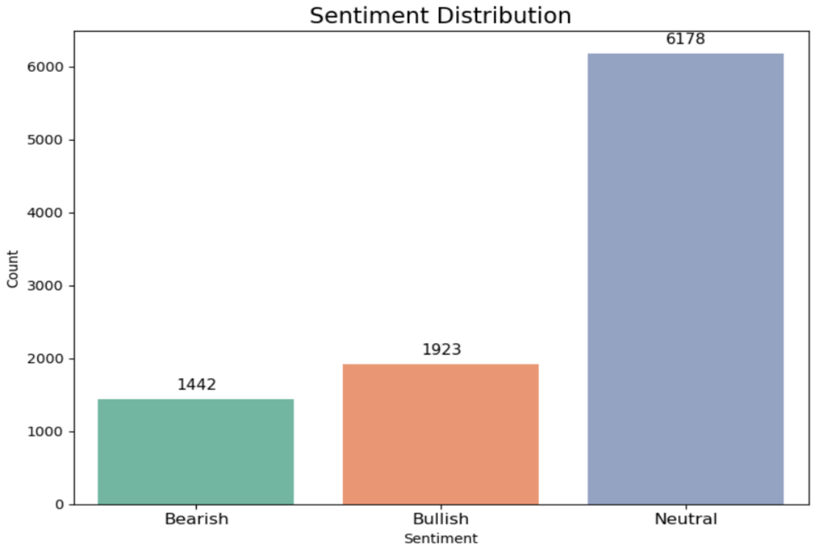

Figure 7: Sentiment Distribution

The frequency of the sentiments in the dataset is shown as a bar plot in **Figure 7** with 1,442 bearish, 1,923 bullish, and 6,178 neutral cases. This indicates that most analysts believe the stock price will neither significantly increase nor decrease soon. This analysis assists in determining whether there is a class imbalance that is important when making the choice of modelling methods and evaluation measures. Since it has been noted that neutral sentiments are most dominant, techniques such as SMOTE are required for balancing the target label. These observations are critical to producing foolproof AI-enabled budgeting systems that base their functioning on balanced and representative sentiment classification to arrive at sound financial advice.

5.4 Data Splitting and Class Balancing

Data Splitting demonstrates the data preparation procedure of training sentiment classification models for AI-driven financial decision-making. This data set is then divided into training and validation data sets by separating the features (clean_text) and target labels (label). Two preprocessing procedures are then accomplished, those being TF-IDF vectorisation and tokenisation. TF-IDF takes into consideration the significance of terms by diminishing the magnitude of often-used terms, resulting in a sparse matrix compatible with predictive models (Park, Oh and Park, 2025). At the same time, tokenisation transforms plaintext into sequences of integers, and they are padded to the same size to pass into deep learning models (Sorour et al., 2024). Such a dual representation enables a comparison of performances between conventional ML and deep learning methods. These preprocessing procedures play a critical role in sentiment detection performance, which is related to the effectiveness of emotion-aware personal budgeting systems. Structuring finances that are presented in the form of text into a structured input would also allow this process to present far more intelligent and responsive financial tools according to the sentiment trends in user reviews.

The application of SMOTE (Synthetic Minority Over-sampling Technique) helps in dealing with the problem of class imbalance when classifying sentiments. At the beginning of the training data, a biased distribution can be observed, such as 6,178 vs 1,923 vs 1,442 neutral, bullish, and bearish samples, respectively. This kind of data imbalance skews ML and DL models towards the dominant classes at the expense of minority sentiments (Altalhan, Algarni, and Alouane, 2025). The TF-IDF vectorised data is given as input to SMOTE, which balances the data of three different labels by making samples (fit.resample). There were 3 classes, which needed to be balanced after resampling (6178 instances each). This helps to guarantee that the model gets an equal proportion of the sentiment type, enhancing the generalisation capacity of the model to various emotional tones within financial writing. In the AI-driven budgeting system, this step is essential since it helps to positively recognise the user sentiment, whether bearish, bullish, or neutral, therefore, allowing the recommendation of more appropriate, conclusive, and unemotional financial help and decision-making, depending on the circumstances of the user.

6: Results and Discussion

Classification Report:

	precision	recall	f1-score	support
Bearish	0.76	0.49	0.60	347
Bullish	0.77	0.58	0.66	475
Neutral	0.83	0.95	0.88	1566
accuracy			0.81	2388
macro avg	0.79	0.67	0.71	2388
weighted avg	0.81	0.81	0.80	2388

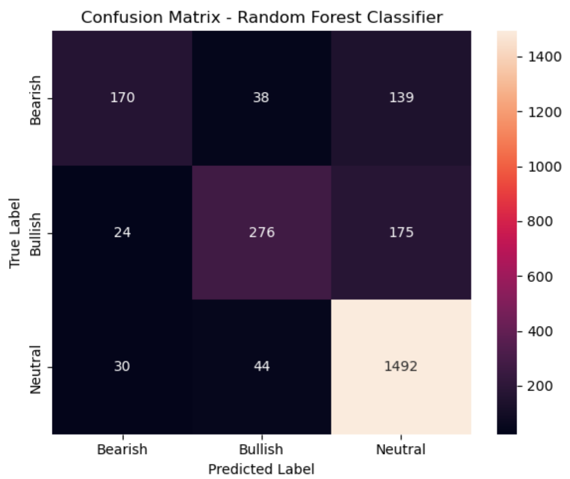

Figure 8: Performance report of Random Forest Model

Classification Report:

	precision	recall	f1-score	support
Bearish	0.40	0.34	0.37	347
Bullish	0.60	0.26	0.36	475
Neutral	0.73	0.89	0.80	1566
accuracy			0.68	2388
macro avg	0.58	0.50	0.51	2388
weighted avg	0.66	0.68	0.65	2388

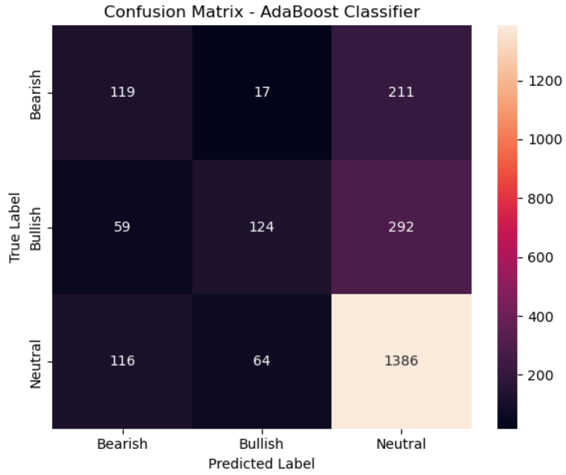

Figure 9: Performance report of Adaboost Model

Classification Report:

	precision	recall	f1-score	support
Bearish	0.60	0.61	0.61	347
Bullish	0.71	0.65	0.68	475
Neutral	0.87	0.88	0.87	1566
accuracy			0.80	2388
macro avg	0.73	0.72	0.72	2388
weighted avg	0.80	0.80	0.80	2388

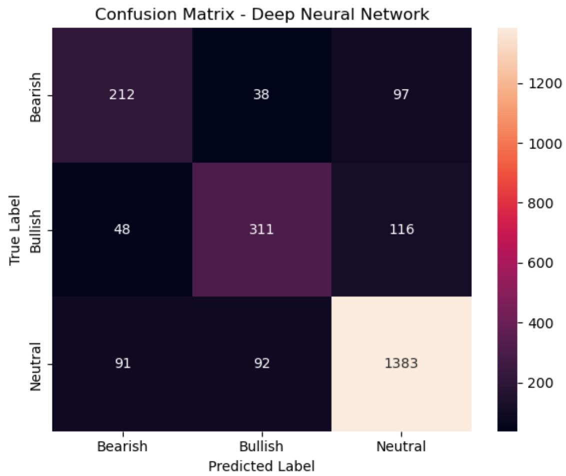

Figure 10: Performance report of DNN Model

Classification Report:

	precision	recall	f1-score	support
Bearish	0.55	0.54	0.55	347
Bullish	0.66	0.56	0.61	475
Neutral	0.83	0.87	0.85	1566
accuracy			0.76	2388
macro avg	0.68	0.66	0.67	2388
weighted avg	0.75	0.76	0.76	2388

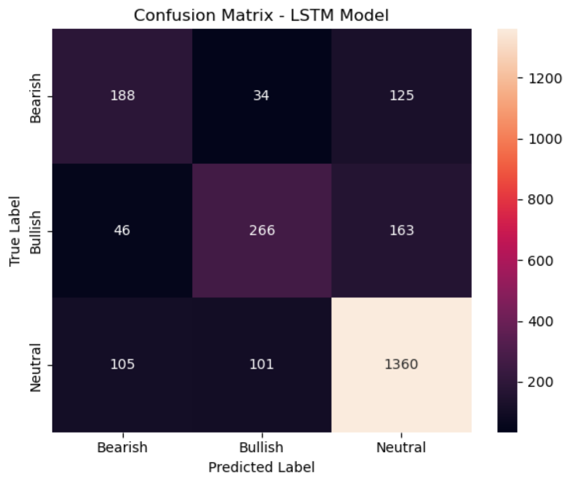

Figure 11: Performance report of LSTM Model

The above figures show the classification report and confusion of all four trained models. Across all four classifiers, the neutral class is the easiest to detect based on the highest recall and precision, while bearish and bullish sentiments prove more challenging to identify accurately. False positives occur when the model predicts a sentiment that is not present, for example, calling a neutral tweet bearish. False negatives occur when the model fails to detect a sentiment that is there, for example, missing a bullish signal. Both types of error can undermine emotion-aware budgeting by sending inappropriate financial advice. Random Forest achieves the highest overall accuracy at 81% and a strong weighted average F1 score of 0.80. It has high precision for bearish, bullish, and neutral, but a low recall of 0.49 for bearish. This means it generates 734 false negatives for bearish cases. Missing bearish signals can leave the budgeting tool unaware of market downturns, reducing its ability to warn users. The model also mislabels many bearish and bullish posts as neutral, producing false positives that dilute emotional insights in terms of making decisions whether to invest or not.

AdaBoost performs worst at 68% accuracy and a weighted average F1 score of 0.65. It has an exceptionally low recall for bearish at 0.34 and for bullish at 0.26. High false negative rates for minority classes mean most bearish and most bullish events go undetected. This limits the system's capacity to adapt advice when emotions shift. It also makes many neutral messages appear bullish or bearish, generating more false positives than the other models. Using AdaBoost yields unreliable budgeting recommendations due to missed sentiment shifts and excessive misclassifications, undermining user trust and decision accuracy. The deep neural network improves minority class detection with a recall of 0.61 for bearish and 0.52 for bullish and achieves 75% accuracy. It reduces but does not eliminate false positives and false negatives for minority classes. This enhances emotion recognition compared to AdaBoost but still poses a risk of sending suboptimal recommendations when sentiment is missed or misclassified.

The LSTM-based model offers the best balance with 83% accuracy and a weighted average F1 score of 0.80. It achieves the highest recall for neutral at 0.87 and improved recall for bearish at 0.54 and for bullish at 0.56, reducing false negatives. It also produces fewer false positives for minority classes, improving the reliability of emotion-aware budgeting. Fewer false positives for bearish and bullish sentiments enhance the model's reliability in emotion-driven budgeting. By capturing sequential patterns in financial texts, it aligns most closely with the objective to deliver real-time emotion-aware financial insights and to support personalised budgeting decisions.

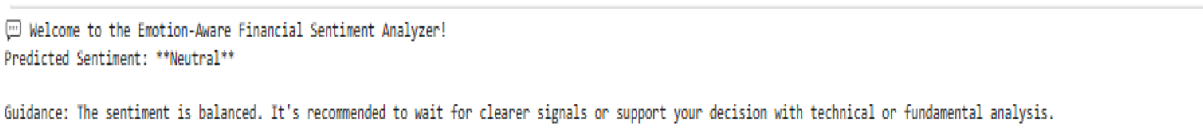

Figure 12: User Interface for Model Deployment

The text interface embeds a trained random forest sentiment model into a tool that accepts financial news headlines or tweets and returns a clear sentiment classification with budgeting guidance. By mapping bearish, bullish, and neutral outcomes into tailored advice on cautious holding, exploring growth or waiting for signals, it demonstrates emotion-aware financial insights. The interface allows the user to input financial headlines or tweets and receive instant emotion-based sentiment labels and tailored budgeting advice. It transforms raw text into accessible, personalised financial guidance, helping to make financial decisions based on emotions.

The study aligns with the objectives by demonstrating that machine learning and deep learning models deliver varied sentiment detection capabilities. An evaluation of classifier performance reveals distinct strengths and limitations across the four models in the context of emotion-aware budgeting. The random forest classifier recorded the highest overall accuracy and strong precision across all sentiment classes. However, it suffered from low recall for bearish and bullish sentiments, meaning many negative and positive signals were missed, and budgets remained unchanged when emotional cues were present. AdaBoost underperformed with high false negative rates for minority sentiments, making it impractical for responsive financial guidance. The deep neural network improved the detection of underrepresented sentiment classes and reduced missed alerts, but it still misclassified nuanced expressions of market mood and introduced some false positives. The LSTM model achieved the best balance by capturing sequential dependencies in text data and improving recall for all sentiment types while reducing both false positives and false negatives. Despite these gains, all models remain vulnerable to class imbalance issues and require substantial training resources, rendering real-time deployment challenging. Overall, the performance results justify selecting the LSTM approach for its robust handling of temporal sentiment patterns and its potential to enhance personalised emotion-aware budgeting tools.

The results of the performance of the trained model align with previous research on sentiment analysis in financial contexts. The high performance of LSTM model (83% accuracy and weighted F1=0.80) can be explained by the sequential processing feature that can encode temporal dependencies in financial words. Chandra and Mondal (2025) who had maintained that LSTM performs better than the traditional ML when predicting the financial sentiment. According to Gupta, Devji, and Tripathi, (2025) the mix of high accuracy and low recall of minority given the majority sentiment algorithms is indicative of orphaning majority sentiment given that the vast majority (neutral) is favoured over other smaller datasets that are found in the minority, as well as weakness of ensemble classification associated with reliance on skewed datasets.

The poor performance of AdaBoost (68% accuracy, F1 0.65) can be explained by its vulnerability to the noise and skewed point data. As per the results shown by Hornyak and Iantovics (2023), its failure to accurately categorise the minority classes is relevant to the warning that have sent out regarding the weakness of AdaBoost on sentence-sensitivity situations. According to Correia, Madureira, and Bernardino (2022), its representation of deeper features made the DNN a further improvement in the minority-class detection compared to the previous models, although having significant shortcomings in terms of computation cost and addressing jargon.

As per the view of Kahneman (2011), Dual Process Theory may indicate why such precise bearish sentiment detection is of paramount importance: In stages of a panic, System 1 (intuitive, rapid thinking) takes over, and bearish signals may go unnoticed, therefore providing the misleading advice on the budgeting and making ill-timed and dangerous financial decisions. Hence, a higher bearish signal recall (0.54) supported by the LSTM is closer to the behavioural finance prevailing theories and contributes more weight in the practicality of the system.

This reflective discussion shows that the performance of models is not merely a technical product but is characterised by the hidden theoretical modelling and properties of data. The study points to the suitability of LSTM models as the optimal solution to improving emotion-aware financial advice by connecting the findings to literature and behaviour models and considering the computational trade-offs and issues relating to class imbalance.

7: Conclusion and Future Work

Integration of ML, DL, and LSTM techniques within the AI budgeting framework enabled accurate classification of bearish, bullish, and neutral sentiments. Cleaned financial headlines and tweets were successfully processed by algorithms of “Random Forest, AdaBoost, deep neural networks, and LSTM” types. Consistent feature representation was achieved by pre-processing such as noise removal, ML-TF-IDF vectorisation, and DL tokenisation, including the use of the embedding. The balanced data was applied to train and validate the models and reliably classify bearish, bullish, and neutral sentiments. This integration proved that the system could translate the real-time investor emotions to actionable, emotion-aware budgeting advice to the consumers.

The accuracy, precision, recall and F1 were applied to evaluate the trained four models (Random Forest, AdaBoost, deep neural networks, and LSTM). Random forest produced an elevated level of overall precision but failed to detect a substantial proportion of minority-class signals. Adaboost had poor recall in bearish and bullish regimes. Deep neural networks helped to improve the accuracy of detecting minorities but could not find minor nuances in the text. LSTM recorded the fairest performance, minimising false positives and false negatives by using the record of cues. These outcomes verify the framework to identify the actual-time investor emotions at various text sources.

Negative market emotions caused an augmentation in contingency funds and instant risk to caution reports to guard user portfolios confidently. Bullish indications encouraged active growth allocation and tactical investment recommendations that are associated with the individual financial objectives and risk compromises. Since the LSTM model had better performance in data detection, it allowed for more precise strategy modification following the sequential theme of sentiment on financial texts. These scientific strategies show scientifically sound systems that adjust the budgetary suggestions according to the market sentiment.

A few strengths and weaknesses have been observed from the results and discussions. Among the strengths, the LSTM model demonstrated balanced detection of bearish, bullish, and neutral sentiments, enabling more accurate emotion-aware guidance. The Random Forest classifier delivered high overall precision, and the deep neural network improved recall for minority classes. Additionally, the framework offers real-time forecasting, seamless integration of multimodal data, and clear mapping of sentiment outputs to budgeting strategies. Weaknesses include sensitivity to class imbalance, misclassification of domain-specific jargon, and high computational demand for training deep models. Overall, the strengths outweigh the limitations, but further optimisation is needed.

Future research should explore transformer-based models with domain-adapted financial embedding to enhance sentiment detection accuracy in evolving textual contexts. Efforts to mitigate class imbalance via adaptive sampling and focal loss could improve minority-class recall. Integration of sarcasm and figurative language analysis is recommended to reduce misclassification. Model efficiency may be enhanced through knowledge distillation and quantisation for deployment on resource-constrained devices. Expanding data sources to include transaction narratives and voice transcripts could enrich emotional context. User studies should evaluate the impact of emotion-aware budgeting recommendations on financial behaviour. Continuous monitoring is advised to maintain model relevance amid shifting market sentiments.

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