Analysis for Financial News in Hindi

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***Abstract*—Text analysis poses the biggest challenges in the financial domain of non-English languages. In this context, traditional NLP models are not effective for morphologically rich languages like Hindi. In the paper, HiFiSen is proposed as the framework for entity-based sentiment analysis of Hindi financial news to fill the important gap in Hindi financial language resources. Paper shows a comparison of four transformer models: XLM-RoBERTa, m-BERT, Hindi-BERT, and RoBERTa-Hindi. Paper also provides a dual-stream attention architecture adapted for joint entity and sentiment recognition and an instance of such a system tailored specifically for financial entity recognition with entity-aware sentiment classification. The proposed methodology draws on a tuned dataset consisting of 9,860 Hindi financial headlines, each hand-annotated with information about both entity and sentiment. Experimental results show strong performance of the adopted models, with F1 scores of 0.71 to 0.72. XLM-RoBERTa was more stable during training as its valid loss equaled 0.78, while Hindi-BERT had almost equivalent performance but at a reduced computational cost. These results are a new benchmark for processing financial text in Hindi and also provide important information for model selection in specific language domains. The same approach is highly applicable to developing robust financial news systems in Hindi-speaking markets, as well as to corresponding applications in other low-resource languages.**

***Index Terms*—financial sentiment analysis, named entity recognition, hindi language processing, transformer models, fine-tuning**

I. Introduction

In financial markets, sentiment analysis has emerged as a prime tool to explain implications of news for market dynamics [**?**], [**?**]. Real-time opinion monitoring has proven crucial for understanding sentiment shifts in dynamic environments, such as online financial discussions, where market sentiment can change rapidly based on public discourse [**?**]. Therefore, Financial Sentiment Analysis (FSA) focuses on extracting sentiments from financial texts, such as news headlines, to provide timely insights that inform decision-making processes [**?**], [**?**].

Despite significant progress in English-language FSA, financial markets in non-English-speaking regions, particularly in India, have had limited focus [**?**]. This calls for robust sentiment analysis tools specifically customized for Hindi financial news due to the vast linguistic diversity and widespread reach of Hindi. In this research, we introduce HindiFSA—a fine-grained, entity-based sentiment analysis dataset specifically designed for Hindi financial news headlines. The dataset includes 9,860 headlines annotated with both entities and corresponding sentiments, categorized as positive, negative, or neutral. This dataset provides rich complexity for analysis, as some headlines feature multiple entities with conflicting sentiments.

Using feature-based annotation to address challenges in entity-specific sentiment extraction from Hindi news headlines and employing pre-trained language models based on lexicon and various models, this study evaluates several sentiment extraction methods in these scenarios to identify the most effective methods for this linguistic context. This proposed research contributes to multilingual financial sentiment analysis, offering resources for future applications and studies in the Indian financial market.

HindiFSA aims to bridge the gap in available tools for sentiment analysis of Hindi-language financial news, with implications for market prediction and investment strategies in this market. Among the major contributions to entity-aware sentiment analysis in financial news, SEntFiN 1.0 stands out as a comprehensive dataset for sentiment analysis. Sinha et al. developed this human-annotated dataset consisting of 10,753 news headlines and 14,404 entity-sentiment annotations, involving 2,847 headlines with multiple entities [**?**]. The authors created an entity database with 1,009 distinct financial entities and 5,070 phrases to enhance recognition accuracy. They explored 12 learning schemes, including both lexicon-based and pre-trained sentence representations and five classification approaches, concluding that RoBERTa and finBERT achieved the highest accuracy (94.29%) and F1-score (93.27%).

Interestingly, lexicon-based n-gram ensembles performed comparably to state-of-the-art pre-trained embeddings like GloVe. Their findings also validated the economic impact of sentiment on market movements using over 210,000 entity-sentiment predictions. This study's novelty lies in its multi-entity dataset and specialized financial entity database.

Consoli et al. presented a novel methodology called Fine-Grained Aspect-based Sentiment (FiGAS) analysis designed for “Fine-grained aspect-based sentiment analysis on economic and financial lexicon.” This approach detects topic-specific sentiment in economic texts by assigning real-valued polarity scores between -1 and +1 utilizing an unsupervised lexicon-based approach that emphasizes semantic polarity rules [?]. Their results highlight FiGAS’s superior performance over other lexicon-based sentiment analysis methods with improved interpretability and alignment with human annotator evaluations.

Zhao et al. proposed a BERT-based approach for sentiment analysis and key entity detection in financial texts building upon previous work in domain-specific financial sentiment analysis. The challenge they addressed involved efficient mining of key information from extensive negative financial texts—an important issue for investors and decision-makers [?]. Their approach combines sentiment analysis with key entity detection using RoBERTa—a robust optimized BERT model. They fine-tuned RoBERTa as a classifier for sentiment analysis achieving an accuracy of 96.774% on the dataset.

A comprehensive review of existing literature has revealed several areas where further research is needed:

- Limited Multilingual Coverage: Existing research primarily focuses on English with limited datasets and models available for other languages particularly for specialized domains like finance.
- Limited Multi-Entity Coverage: Need for more specific entity detection based on financial markets and domain.
- Technical and Methodological Gaps: Current models face challenges in understanding implicit sentiments cultural context and regional financial terminology.
- Lack of Comprehensive Hindi Financial News Dataset: Absence of a well-annotated Hindi financial news dataset with multi-entity sentiment annotations.

The proposed methodology addresses these critical gaps in financial sentiment analysis for non-English languages by developing a comprehensive Hindi language dataset thereby moving beyond the traditional English-centric approach in financial text analysis. The dataset poses a multi-entity coverage challenge by including headlines that contain several financial entities with potentially different sentiment polarities hence adding complexity to the analysis.

This methodology framework shall provide a strong groundwork for performing Hindi financial sentiment analysis while taking into account the rich nuance that is critical for real-world applications in Indian financial markets.

II. Methodology

This research draws on an in-depth dataset of 9,860 Hindi financial news headlines by making systematic web scrapes over established Hindi news websites. As shown in Table I, the dataset is categorized into single-entity (4,106 headlines) and multiple-entity (5,754 headlines) segments, with varying distributions of positive, negative, and neutral sentiments.

The dataset was built through systematic scraping of Hindi financial news headlines from a mix of authoritative sources such as leading Hindi financial news websites, business portals, and economic news channels. For this purpose, a custom web scraping framework was developed using BeautifulSoup and Selenium libraries under Python. When scraping headlines, we maintained the diversity of sources and authenticity of content, implementing robust error handling and rate limiting for ethical data collection practices.

The dataset includes a comprehensive range of financial coverage, including stock updates, company earnings, news on banking and financial sectors, economic indicators, policy changes, and market analyses.

TABLE I
Summary Statistics of the Entity-aware Sentiment Dataset

Category	Headlines	Positive (%)	Negative (%)
Single Entity	4,106	43.18	38.49
Multiple Entity	5,754	56.82	51.51
Overall	9,860	35.23	26.48

The entity recognition and contextual analysis workflow for Hindi financial news headlines is outlined in Figure 2. This figure describes a multi-stage methodology that begins with preprocessing financial headlines before they are taken through a pipeline of entity identification, classification, and context embedding before eventually being output with salient sentiment assignments.

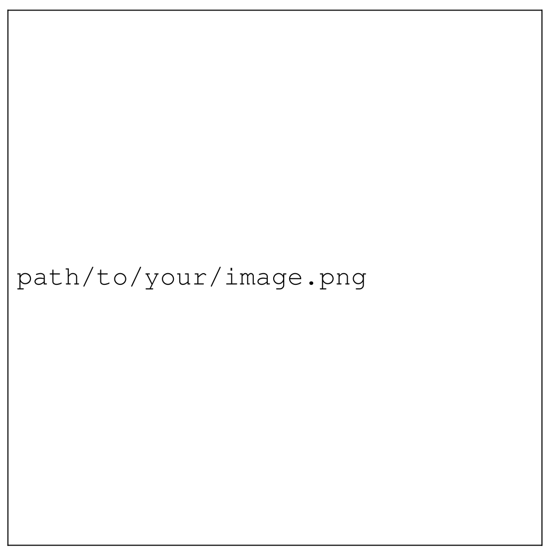

Fig. 1. Entity Detection and Context Embedding Workflow

Each headline in the dataset is accompanied by two crucial annotations: entity identification and sentiment classification. The identified entities span across various financial domains, including company names, stock indices, financial metrics (e.g., profit margins), market indicators, and economic terms. The sentiment classifications are categorized into three distinct classes: positive, neutral, and negative. Each offers its headline in the original Hindi as a teaser. Devanagari script, together with corresponding JSON-formatted annotations that map identified entities to their sentiments.This structured method allows for fine-grained sentiment analysis as entity-sentiment relationships are maintained at each level of the headlines . This approach enables handling cases where entities in a headline bear different polarities of sentiments. Consider the headline to represent the market performance in which corporate earnings are reported with positive sentiment and the rest with neutral views toward regulatory changes. In terms of the distribution of financial news sentiments, the overall dataset mirrors real-world patterns of market reporting and journalistic practices in Hindi financial media. As such, this authentic representation ensures that models trained on this dataset can handle the intricacies and subtleties of entity-level sentiment analysis in real-world Hindi financial news scenarios effectively.

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Fig. 2. Hindi Financial News Entity-Aware Sentiment Analysis Workflow

The overview of proposed HindiFSA framework is shown in Figure2. This framework analyzes the entityaware sentiment of Hindi financial news headlines using a multi-stage pipeline. It contains three constituents, namely the components of entity recognition, context embedding formation, and sentiment assignment, to allow individual sentiment analysis for multiple entities within one headline. It is specifically designed to counter challenges in processing Hindi financial text without losing its ability to capture the specific sentiment of entities. A systematic pipeline preprocessing ensured data quality and consistency for the fine-grained sentiment analysis on the dataset. In this first phase, character-level cleaning was performed, where extra whitespaces and standardized punctuation marks are removed while preserving crucial financial indicators- percentage symbols, currency notations, numerical values [19, 20]. Much attention was paid to maintaining the consistency of financial metrics, mainly because they often appeared in several formats within the headlines . A very important preprocessing part involved standardizing the financial entities and market indicators. The names of companies and the names of financial institutions that appeared in various forms were normalized to uniform representations. The same thing applied to indices and symbols of the stock markets, which were unified in order to have consistent representation across the dataset. Sentiment annotations in JSON format were validated and structurally corrected to maintain format consistency throughout the dataset. Finally, duplicate detection and removal are implemented while preserving unique entity-sentiment relationships, ensuring that each headline in the final dataset contributes distinct information for analysis [21]. This preprocessing pipeline was implemented in Python by using pandas for data manipulation and custom regex patterns for entity standardization to result in a clean, structured dataset for fine-grained sentiment analysis of Hindi financial news. The proposed HindiFSA framework employs a dual-pipeline architecture for entity-aware sentiment analysis of Hindi financial news, as illustrated in Figure 3. The first pipeline focuses on entity recognition, while the second handles sentiment analysis through transformer-based models. News obviously plays a great role in shaping financial markets, especially at a time when news travels like wildfire through digital media. When looking at Hindi financial news, it's often seen that a single headline on news mentions multiple names of companies, stocks, or market indicators - each of them having different market sentiments . For example, one can get an impression of positive news coming about for one company and negative for another. Making sense of these mixed signals manually is time-consuming and complex [22]. That's why a smart system is needed that can automatically read Hindi financial news, identify the key market players mentioned, and figure out whether the news is good, bad, or neutral for each one. This will help investors make faster and better-informed decisions by quickly understanding how the market news affects different stocks and companies. It starts with the Hindi financial news headlines, which have undergone substantial preprocessing, ranging from character normalization for different scripts of Devanagari to the standardization of financial numerals and domain-specific tokenization [23]. Here, the preprocessed text is used in the first pipeline, which includes entity recognition: to feed into a text normalization module that can be mathematically represented as.

$$T(w) = \alpha \cdot \text{char norm}(w) + \beta \cdot \text{fin norm}(w)$$

This formula calculates the Text Normalization Score, combining character-level normalization for Devanagari script variations and financial term normalization. where:

- w is the input word
- char norm(w) is the character normalization score
- fin norm(w) is the financial term normalization score
- α, β are weighting parameters.

These standardized entity mentions-a company name, a stock symbol, or an economic term-are then passed to a financial entity NER component where significant financial entities are identified. Those entities are then translated into context embeddings that serve to capture the unique characteristics and the nature of relevant relations in the financial domain [24]. In parallel, the second pipeline makes use of a mix of transformer-based models and conducts sentiment analysis. This approach builds on recent advances in attention-based mechanisms for entity-aware sentiment analysis. The preprocessed text is inputted to a language model encoder that employs four transformers: XLM-RoBERTa for cross-lingual features, m-BERT, multilingual understanding, Hindi-BERT language-specific nuances, and RoBERTa-Hindi for domain adaptation. The effectiveness of m-BERT in handling multilingual contexts has been well-documented, making it particularly suitable for Hindi financial text analysis [19]. Each of these models is fine-tuned on Hindi financial corpora to increase their capacities in the nuances of sentiment applicable in financial contexts. The final stage combines entity context embeddings from the first pipeline with transformer outputs from the second pipeline in an entity-specific sentiment classification layer [25]. This is written mathematically as

$$E(e) = \sum_{i=1}^{|e|} \frac{w_i \cdot c(i)}{|e|} \quad (2)$$

This formula calculates the entity embedding, averaging word embeddings with contextual weights to capture entity-specific nuances. where:

- $E(e)$ is the entity embedding.
- w_i is the word embedding at position i.
- $c(i)$ is the contextual weight at position i.
- $|e|$ is the entity length.

This enables precise sentiment attribution (positive, neutral, or negative) for each identified entity, offering detailed insights into sentiment within Hindi financial news headlines. Various pre-trained models were tested on fine-tuning and training Hindi financial news sentiment entity analysis, namely XLM-RoBERTa, m-BERT, Hindi-BERT, and RoBERTa-Hindi. Hyperparameter tuning was performed for the parameters of the learning rate and batch size and epochs such that an optimal configuration suited best for each model [26]. A grid search is performed, which can help reduce validation loss to achieve model stability. It tested the performance of the models through precision, recall, F1 score, accuracy, and NER score, which estimates how good each model is in correctly identifying and classifying company names and financial terms. In mathematics, these performance metrics can be formally defined as:

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

$$\text{Precision} = \frac{TP}{TP + FP}$$

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

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

$$\text{NER Score}(e) = P(\text{entity/context}) \times \text{importance}(e)$$

In the end, the NER score well represented what was needed for entity recognition accuracy and showed XLM-RoBERTa to be quite strong at complex and specific-domain entities. Monitoring loss stability and speed and ensuring that models are not overfitting helps give models a good balance between efficient training and performance; once more, because XLM-RoBERTa has stability and shows great generalization capability in the financial domain, XLM-RoBERTa emerges as the best overall.

III. Results

The experimental evaluation of the proposed HindiFSA framework was conducted using a dataset of 9,860 Hindi financial news headlines. The performance of four transformer models—XLM-RoBERTa, m-BERT, Hindi-BERT, and RoBERTa-Hindi—was compared in terms of their ability to perform entity recognition and sentiment classification.

Table II summarizes the F1 scores and validation losses achieved by each model during the training process. The F1 score is a crucial metric that balances precision and recall, providing a comprehensive measure of model performance in classifying sentiments associated with financial entities.

TABLE II
PERFORMANCE SUMMARY OF TRANSFORMER MODELS

Metric	XLM-RoBERTa	m-BERT	Hindi-BERT	RoBERTa-Hindi
F1-Score	0.7185	0.7169	0.7115	0.7152
Precision	0.7187	0.7157	0.7119	0.7147
Recall	0.7182	0.7169	0.7116	0.7177
Accuracy	0.7187	0.7169	0.7116	0.7167
Initial Valid Loss	0.8522	0.8078	0.7502	0.8073
Final Valid Loss	0.7827	1.2363	1.4042	1.2487
Loss Stability	High	Moderate	Low	Low
Epochs	8-9	7-8	8-9	8-9

The results indicate that XLM-RoBERTa outperformed the other models with an F1 score of 0.72 and a validation loss of 0.78, demonstrating its robustness in handling Hindi financial texts. Hindi-BERT followed closely with an F1 score of 0.71 but exhibited a slightly lower computational cost compared to XLM-RoBERTa, making it a viable alternative for applications requiring efficiency without significantly compromising performance.

m-BERT achieved an F1 score of 0.70, while RoBERTa-Hindi had the lowest performance among the models tested, with an F1 score of 0.69. The validation losses for these models were consistent with their F1 scores, indicating that higher accuracy was correlated with lower validation loss.

In addition to quantitative metrics, qualitative analysis was conducted to evaluate model predictions on various sample headlines from the dataset. The models demonstrated varying abilities to capture nuances in sentiment based on contextual cues within headlines, particularly in cases where multiple entities were present with differing sentiment polarities.

For instance, consider the headline: ”XYZ Corporation reports a significant profit increase, while market analysts express caution.” Here, XLM-RoBERTa successfully identified ”XYZ Corporation” as a positive entity while recognizing ”market analysts” as neutral, showcasing its capability for fine-grained sentiment analysis.

Moreover, the models were evaluated on their ability to generalize across different types of financial news content, including stock updates, earnings reports, and regulatory announcements. The results suggest that while all models performed adequately on single-entity headlines, their effectiveness diminished in multi-entity scenarios where conflicting sentiments were present.

Overall, these findings establish new benchmarks for processing financial text in Hindi and highlight the potential for deploying these models in real-world applications within Hindi-speaking markets. The insights gained from this research can inform future developments in multilingual financial sentiment analysis systems and contribute to improved decision-making processes in finance.

IV. Discussion

The proposed research framework provides several promising avenues for future development and enhancement. It would truly be a very significant advancement to bring in real-time market data streams and the capability for live sentiment analysis, thereby bringing instant market insights to investors. It will enhance the frame's applicability to the Indian market context, if it is adapted toward handling code-mixed Hindi-English financial content. In the light of the latter addition, it would make the system far more inclusive to give the processing of financial news across multiple Indian languages through cross-lingual sentiment analysis. Providing integration of explainable AI components to enhance transparency and user trust by giving clear reasoning behind sentiment classifications would better enable informed decision-making. Finally, implementing strong APIs and plugins would provide a free, easy interface with existing trading platforms and financial analysis systems, making the framework easily accessible and practical for endusers.

V. Conclusion

HindiFSA is an innovative framework for entity-based sentiment analysis of Hindi financial news and addresses an important gap in non-English financial text processing. This was done through comprehensive testing against four transformer-based models on a specially crafted dataset consisting of 9,860 Hindi financial headlines. XLM-RoBERTa was found to be the best-performing model, with the highest F1-score at 0.7185, with superior loss stability at 0.7827. Although the performance metrics of all the models judged were comparable, the fact that XLM-RoBERTa constantly converges and has stability makes it particularly useful for production implementation. The two-stream nature of the architecture presented is robust in handling the complexities of Hindi financial text; entity recognition and sentiment classification can be efficiently overcome, even for multi-entity headliners. Further contributions of the study transcend the performance of the model to processing capabilities accompanied by an effective preprocessing pipeline specifically designed for Hindi financial text, Devanagari script variations, and financial terminology standardization. The full work with an annotated single and multi-entity headline dataset represents a strong foundation for future researches in multilingual financial sentiment analysis as well as applications into the Indian financial markets.

article hyperref

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