NEURAL NETWORK AND HYBRID MECHANISMS IN DATA PROCESSING FOR FINANCIAL ANALYTICS

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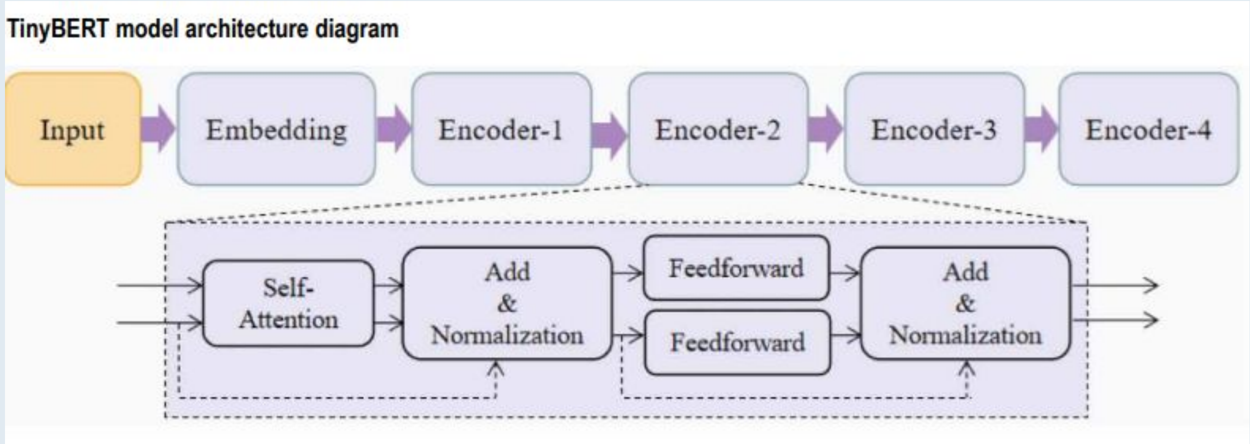
PROBLEM STATEMENT

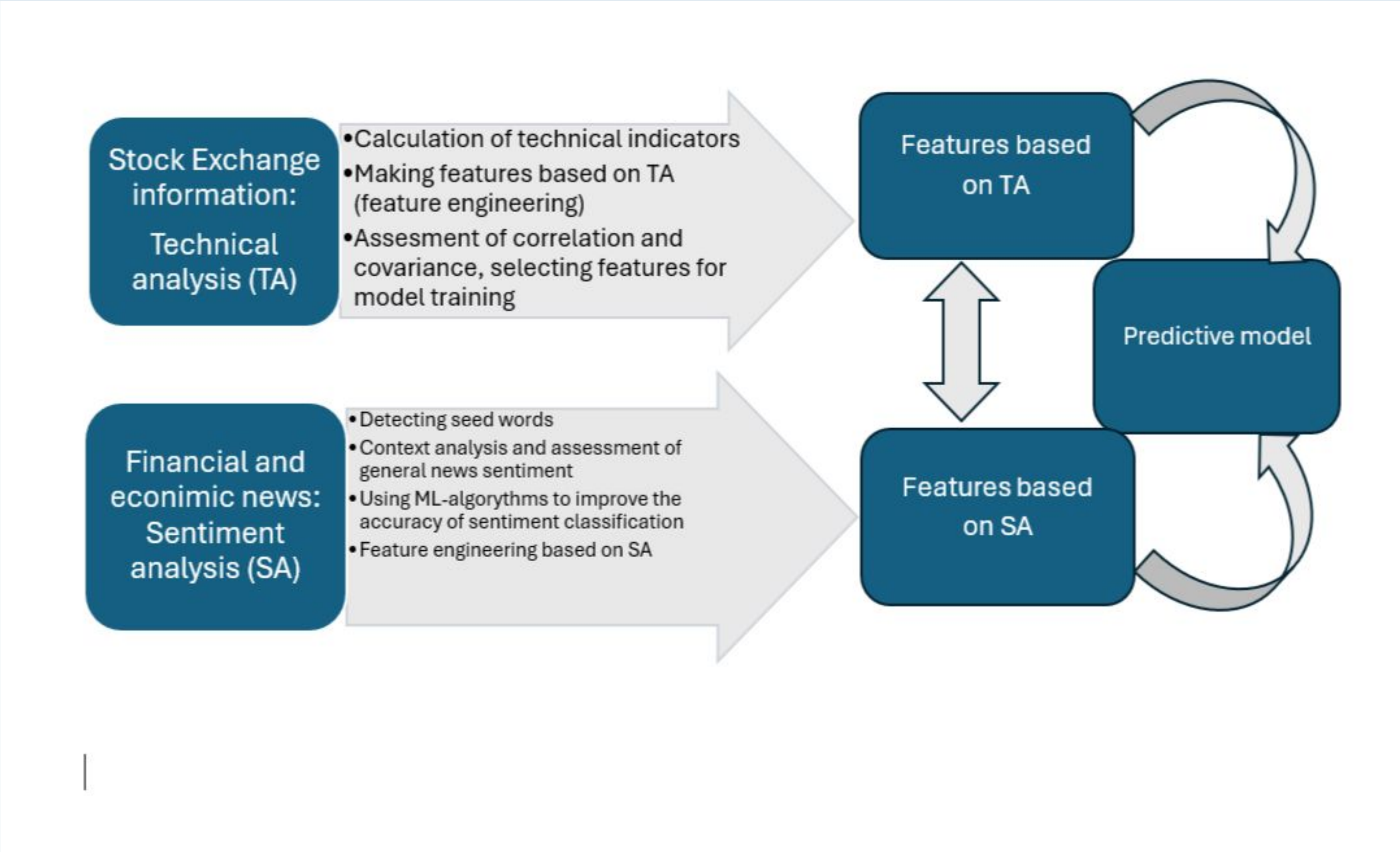
- The current hybrid model's performance in financial sentiment analysis can be improved by adding additional features extracted from social media posts.

GOAL

- Incorporate a new set of features extracted from the sentiment analysis of financial social media posts from Pulse using TinyBert and a Hierarchical Query-driven Attention Network (HQAN).



HYBRID MODEL



DATASET

- DATASET: Telegram Financial Sentiment (RU) (3000 samples)
- Built a dataset from Pulse publications by extracting and labeling financial sentiment
- Compiled 500 samples from Pulse posts with ticker-based labeling
- 308 000 samples in general

```python
def fetch_news(ticker, cursor=''):
    url = f'https://www.tinkoff.ru/api/invest-gw/social/v1/post/instrument/{ticker}?cursor={cursor}&limit=50'
    try:
        response = requests.get(url, headers=HEADERS)
        response.raise_for_status()
        try:
            json_data = response.json()
        except requests.exceptions.JSONDecodeError:
            print(f"Invalid JSON response for ticker {ticker}. Skipping...")
            return [], None

        data = json_data.get('payload', {}).get('items', [])
        next_cursor = json_data.get('payload', {}).get('nextCursor', None)

        news_list = []
        for item in data:
            post_date = datetime.strptime(item.get('inserted'), '%Y-%m-%dT%H:%M:%S.%f%z')
            if 2020 <= post_date.year <= 2025:
                reactions = item.get('reactions', {}).get('counters', [])
                reaction_sum = sum(
                    reaction.get('count', 0)
                    for reaction in reactions
                    if reaction.get('type') in ['like', 'rocket', 'buy-up']
                )

                news = {
                    'ticker': ticker,
                    'post_id': item.get('id'),
                    'owner_id': item.get('owner', {}).get('id'),
                    'date': post_date.strftime('%Y-%m-%d'),
                    'reactions_sum': reaction_sum,
                    'text': item.get('content', {}).get('text', '')
                }
                news_list.append(news)
```

```
9b5-fb8d-480c-9286-ebed145a1fcb,MTSS ❗Дело ФАС против МТС о необоснованном повышении стоимости услуг в марте-апреле 24 не окажет влияния на
3a2-726a-4637-8a2a-635af6804fab,"6,06 руб. на каждую обыкновенную и привилегированную акции, предложения направлены в правительство, сообщил
9f0-4630-43e3-93b0-567969a45b29,"LKOH , видимо инвесторы с открытия брокер нормик зашли. @T-Investments, где дивиденды? Почему Вы держите ден
2ef-44d0-4062-9ea1-fff7dd97b718,"GAZP пробил сопротивление в 170, давай и ты LKOH пробивай своё в 5300)",Neutral,0
d36-5eed-41e4-a208-f607bb8d5c81,"Начинают приходить дивы по LKOH , угадайте, куда они вкладываются?😁",Positive,1
19b-366e-422f-ba60-768204e2e298,LKOH на открытие пришли дивы. Ракета 😁,Positive,1
c4a-acd7-4f3d-b6f0-25f6b0977783,"LKOH красиво полетели, нужно искать точку входа для короткого шорта, думаю 5340 смотрится неплохо",Positive,
```

SUMMARIZATION ATTEMPT

- Tried summarization of texts using when len(text) > 500 → TOO SLOW
- Use ±2 sentences around main ticker → TOO SLOW
- Didn’t improve clarity

```
Summarizing texts:  98%|                                        | 24662/25146 [33:18:58<41:19,  5.12s/ example
```

- So instead considered windows of words around main ticker
- Main tickers: SBER, LKOH, MTSS, GMKN, AFLT, MOEX

MODELS COMPARED

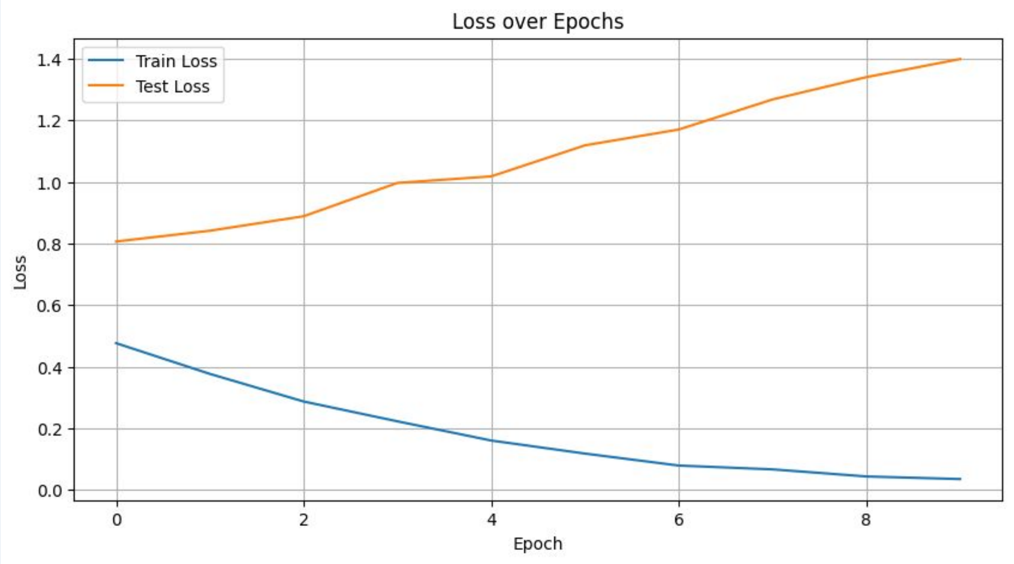
- RUBERT-BASE-CASED-SENTIMENT
- RUBERT-TINY2-RUSSIAN-FINANCIAL-SENTIMENT
- Tested on custom dataset

```
--- Evaluating: blanchefort/rubert-base-cased-sentiment
Predicting with blanchefort/rubert-base-cased-sentiment:
Accuracy: 0.3581
Macro Recall: 0.3582
Macro F1: 0.3227
Weighted F1: 0.3293

Classification Report:
              precision    recall  f1-score   support

     Neutral       0.41      0.56      0.48       216
    Positive       0.43      0.12      0.19       203
    Negative       0.25      0.39      0.30       120

    accuracy                           0.36       539
   macro avg       0.36      0.36      0.32       539
weighted avg       0.38      0.36      0.33       539
```

```
--- Evaluating: mxlcw/rubert-tiny2-russian-financial-sentiment
Predicting with mxlcw/rubert-tiny2-russian-financial-sentiment:
Accuracy: 0.6698
Macro Recall: 0.6583
Macro F1: 0.6560
Weighted F1: 0.6670

Classification Report:
              precision    recall  f1-score   support

     Neutral       0.73      0.60      0.66       216
    Positive       0.66      0.80      0.72       203
    Negative       0.59      0.57      0.58       120

    accuracy                           0.67       539
   macro avg       0.66      0.66      0.66       539
weighted avg       0.67      0.67      0.67       539
```

FINE-TUNING RESULTS

- Up to 15 epoches
- Best results at 4 epoches



	epoch	train_loss	test_loss	accuracy	recall	f1_macro
0	1	0.476560	0.806628	0.667904	0.674182	0.660590
1	2	0.376724	0.841646	0.667904	0.660156	0.661159
2	3	0.287102	0.888720	0.677180	0.675429	0.669500
3	4	0.222675	0.996921	0.660482	0.672107	0.657432
4	5	0.160368	1.018126	0.682746	0.675515	0.675685
5	6	0.117972	1.118986	0.654917	0.658835	0.650947
6	7	0.079078	1.170401	0.671614	0.667194	0.664113
7	8	0.066689	1.267992	0.664193	0.668231	0.658924
8	9	0.043685	1.340437	0.671614	0.677811	0.666223
9	10	0.035230	1.399117	0.647495	0.647823	0.642960

WHAT'S NEXT

- More hyperparameter tuning (Only 1 ticker per text, length of window)
- Expand custom dataset 500+
- Explore and study Interpretable Financial Sentiment Analysis with HQAN
- Compare models by Accuracy and F-1 score

REFERENCES

- [1] Qiu, J., Wu, Q., Ding, G., Xu, Y., Feng, S., & Shi, Y. (2016). A survey of machine learning for big data processing. *Journal of Big Data, 3*(1), 1–17. https://doi.org/10.1186/s40537-017-0111-6
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- [3] Jin, D., Zhang, Y., Zhu, H., He, X., Li, Y., & Wu, J. (2024). Financial sentiment analysis: A survey. *ACM Computing Surveys, 56*(3), 1–38. https://doi.org/10.1145/3649451